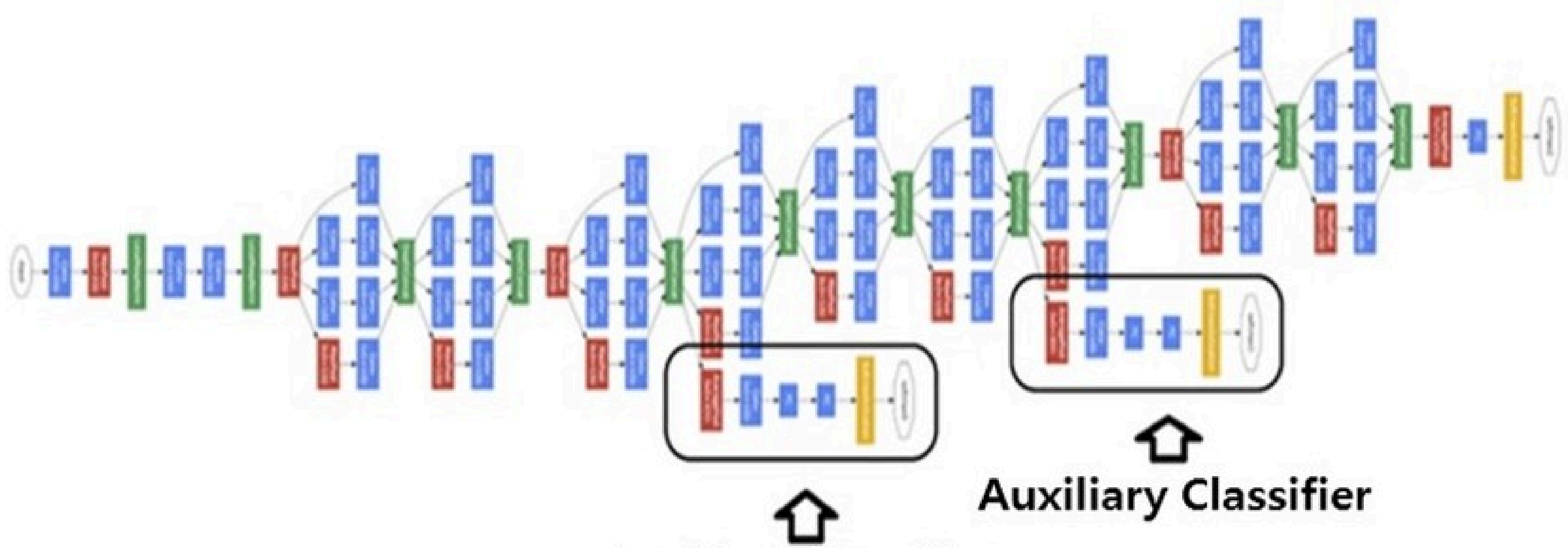
Image Processing 🧠

Success of GoogLeNet

- **The success of GoogLeNet and VGG** shows that *depth* is important.
  - VGG: 19 layers, GoogLeNet: 22 layers
- **Larger networks always perform better** 😎

Well It all makes sense, right?



But it is not that simple! 🤔

Paradoxically, deeper networks beyond 20 layers showed *higher* training error than shallower ones.

What's the problem?

- In theory, deeper networks are more powerful and expressive.
- In practice, not!
- Two problems:
  - **Degradation Problem:** Training becomes unstable and harder.
  - **Vanishing/Exploding Gradients:** Error signals struggle to propagate back through many layers, even with ReLU and auxiliary classifiers.
- Note that this is not because of overfitting but more fundamental issues.

Shouldn't deeper networks, with more capacity, learn at least as well as shallower ones?

A remedy for the degradation problem ~ Batch Normalization

center

Internal Covariate Shift

What is it?

The distribution of a layer's inputs changes during training because the parameters of preceding layers are constantly changing.

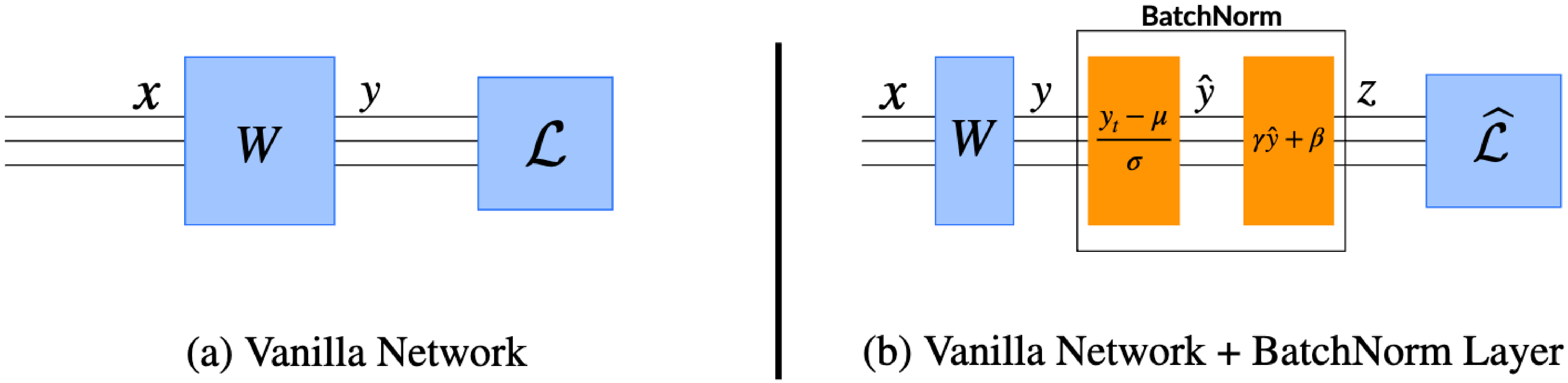
Why is it bad?

1. **Slows Training:** Each layer must adapt to a shifting input distribution.
2. **Requires Careful Initialization:** Networks become very sensitive to the initial weights.
3. **Needs Lower Learning Rates:** High learning rates can amplify the shifts, causing gradients to explode or vanish.

The Core Idea: Normalize Activations 💡

How?

For *each feature* (channel) independently normalize the activations within the **current mini-batch** to have **zero mean** and **unit variance**.



> Timely paper from @ShibaniSan, Dimitris Tsipras, @andrew_ilyas , and @aleks_madry providing some new insights into why batch norm works. They perform a number of clever experiments to work it out, finding that internal covariate shift is a red herring! https://t.co/fJV4DjagW5 pic.twitter.com/G20yf9pMeJ
>
> — Ari Morcos (@arimorcos) May 30, 2018

How Batch Norm Works (During Training) ⚙️

For a mini-batch $B = \{x_1, \ldots, x_m\}$ and a specific activation feature:

1. **Calculate Mini-Batch Mean and Variance:**

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i, \quad \sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2$$

2. **Normalize:** (Add small epsilon ϵ for numerical stability)

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

3. **Scale and Shift:** Introduce learnable parameters γ (scale) and β (shift).

$$y_i = \gamma \hat{x}_i + \beta$$

- γ and β are learned during backpropagation just like weights.
- Applied independently to each feature/channel dimension.

Does this remind you of something?

Batch normalization

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

Why Scale and Shift? (Gamma γ & Beta β) 🤔

> 🤔 **Question**
>
> If we just normalized to zero mean/unit variance, why add learnable scale (gamma) and shift (beta) parameters?

Batch Normalization

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

💡 **Answer**

Always normalizing to zero mean and unit variance could **restrict what the network can learn**.

- Some activation functions work better with inputs in specific ranges.
- γ **and** β **let the network adjust the scale and shift as needed.**
- If helpful, the network can even learn to undo normalization completely.
- This gives the model more flexibility to find optimal representations.

Do you remember?

> 🤔 **Question**
>
> Do you remember how to compute the mean and variance parameter?

Batch Normalization

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

How would you compute them for inference?

🤔 **Question**

During inference, we often process images *one by one* (or in small, non-representative batches). How would you compute the mean and variance parameters?

Batch Normalization

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

💡 Answer

- During training, BN layers maintain **running averages** of the mean (μ) and variance (σ^2) across *all* mini-batches seen so far.
  - `running_mean = momentum * running_mean + (1 - momentum) * batch_mean`
  - `running_var = momentum * running_var + (1 - momentum) * batch_var`
- At **inference time**, use these fixed, *population* statistics ($\mu_{pop}, \sigma^2_{pop}$) instead of mini-batch statistics for normalization:

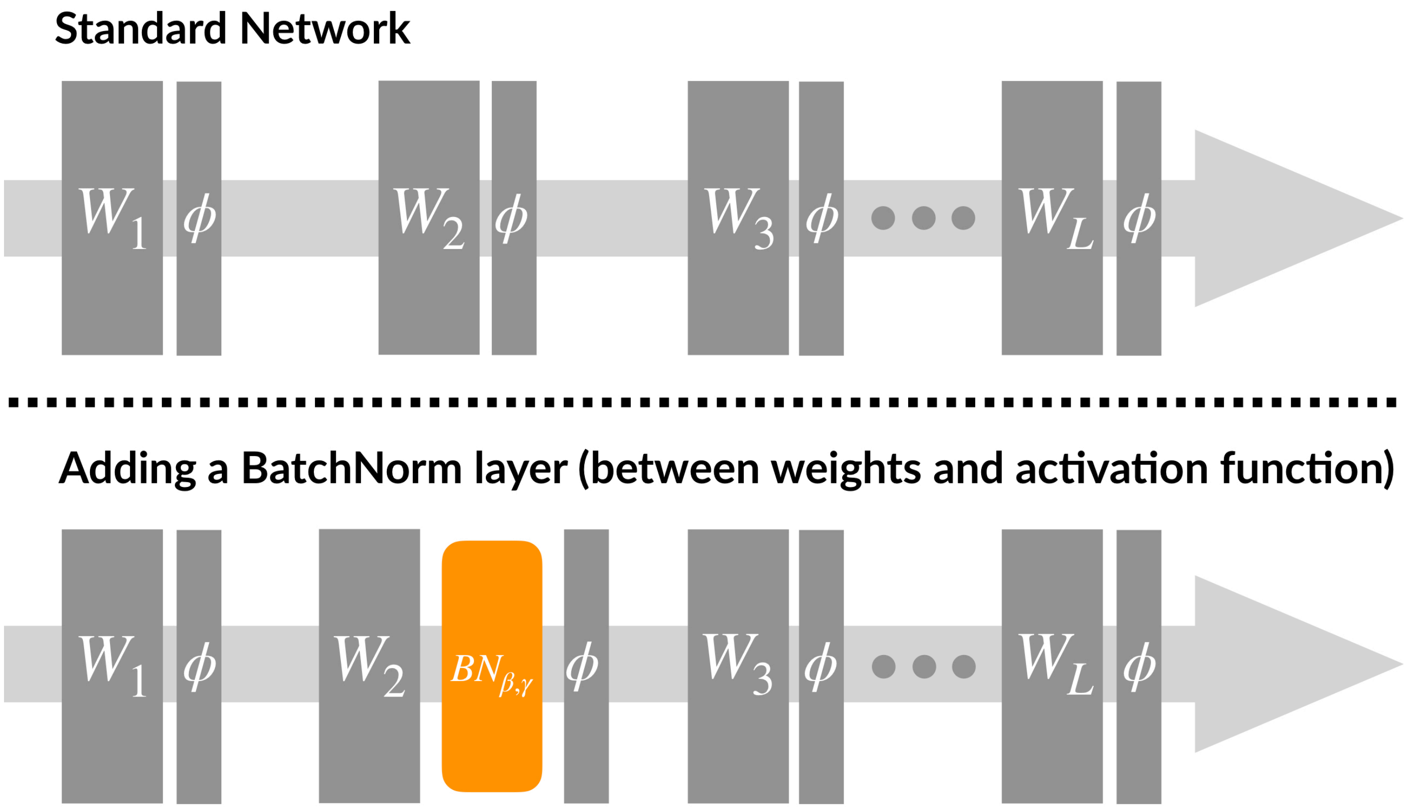
$$\hat{x} = \frac{x - \mu_{pop}}{\sqrt{\sigma^2_{pop} + \epsilon}}$$

$$y = \gamma \hat{x} + \beta$$

- The learned γ and β are still used.

Placement of Batch Norm Layer 📍

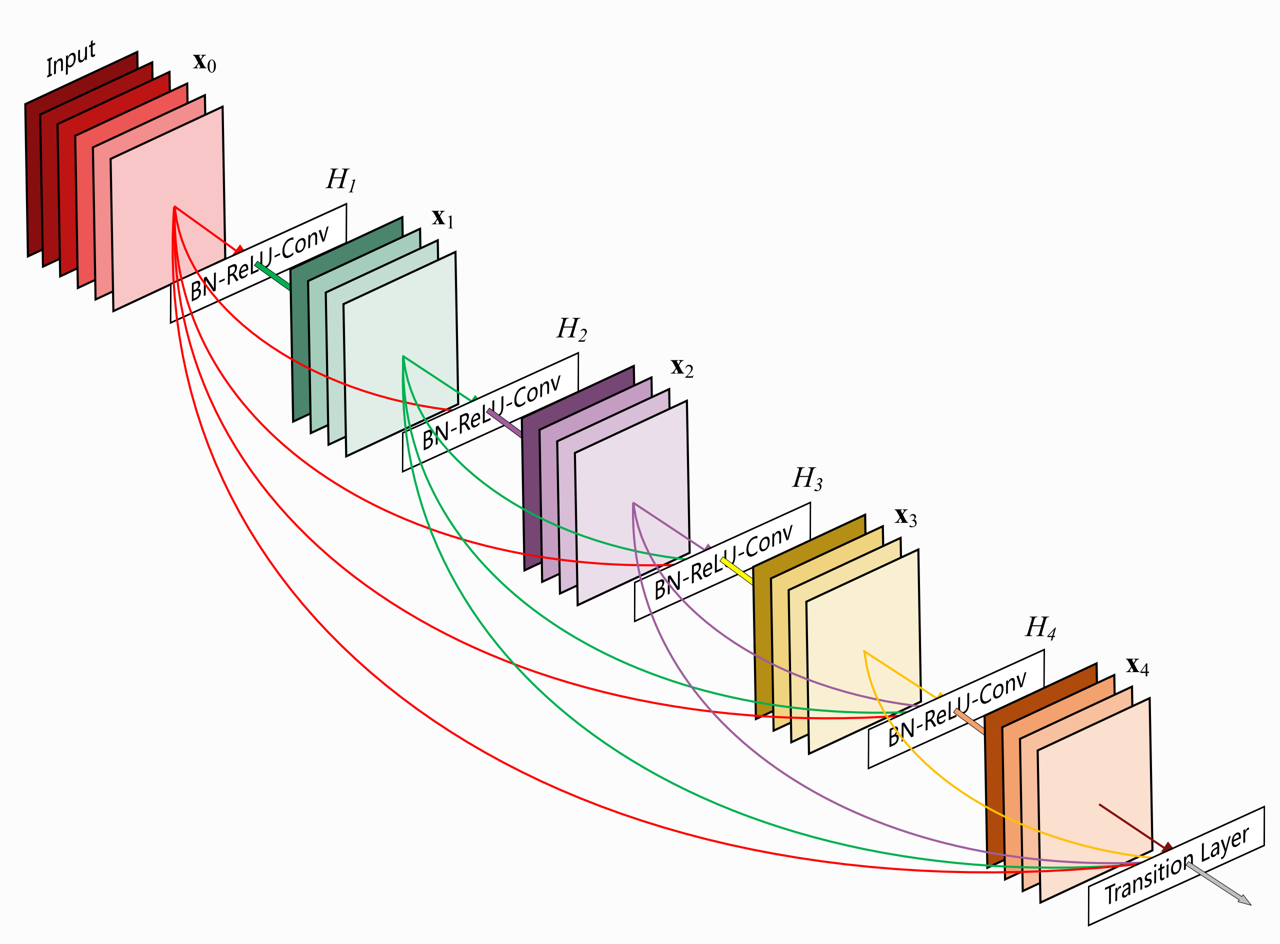
- Common practice: Apply BN **after** the Convolutional or Fully Connected layer and **before** Activation function (e.g., ReLU).
- Variation exists! (such as BN after activation)



A remedy to vanishing gradient problem ~ Skip-connections

ResNet

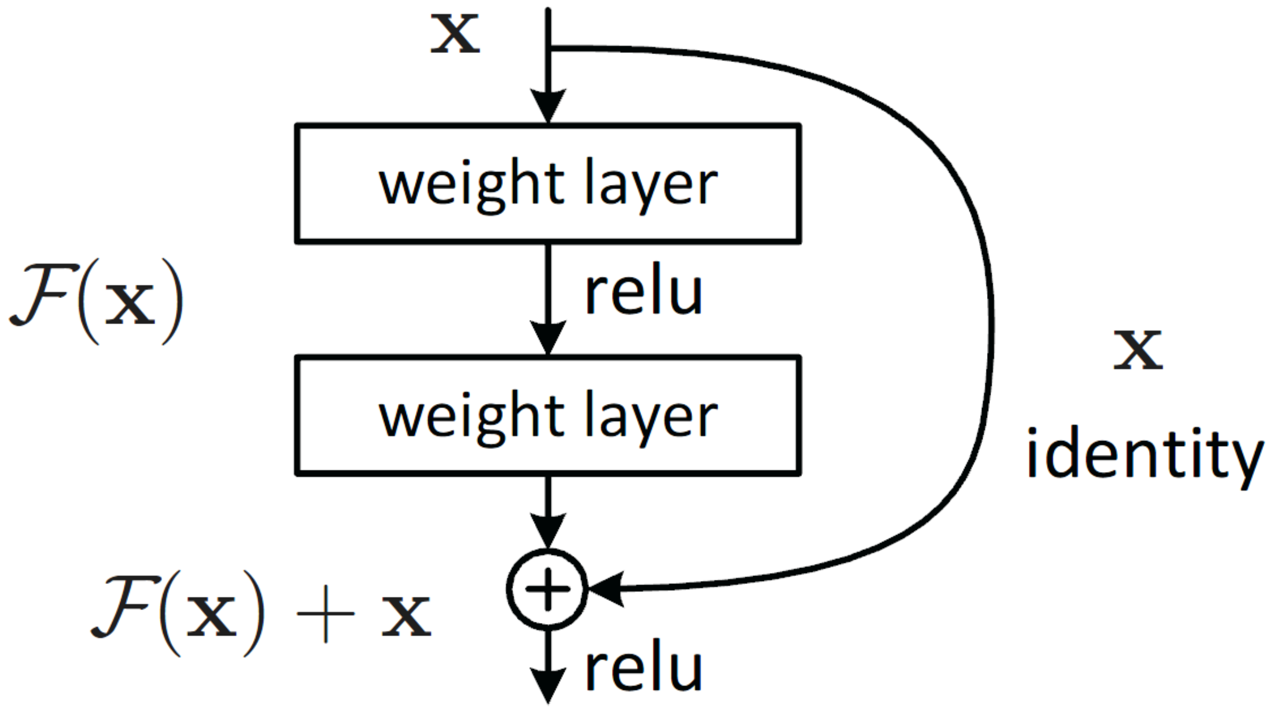
- A simple but transformitive idea: adding a direct connection from the input to the output (a.k.a. **skip-connection**)
- Enabled training of *extremely* deep networks (50, 101, 152+ layers).
- Overcame the **vanishing gradient** and **degradation problems**.
- One of the most influential deep learning innovations.



The Core Idea: Residual Learning 💡

- **Key idea**:
  From multiplicative to additive transformations
- Formula:
  From $y = F(x)$ to $y = F(x) + x$, where F is a neural net.

The network learns the **difference** needed, adding it back to the original input via a **skip connection**.



Why Residual Connections Work?

Reason #1: Easier Optimization via Identity Mapping ✅

- **Identity mapping** maps data x to x itself.
- Identity mapping is hard to learn for *multiplicative* transformation but easy for *additive* transformation.
    - Often the weights in neural nets are initialized to be close to zero.
    - In the additive case, the default is close to identity mapping!
- $F(\mathbf{x})$ can still learn complex transformations if needed.

Reason #2: Better Gradient Flow 🌊

🤔 **Question**

Let's consider two layers with skip connections:

$$y = F(x) + x$$

and

$$z = G(y) + y$$

Derive the gradient of z with respect to x.

💡 **Answer**

$$\frac{\partial z}{\partial x} = \frac{\partial G(y)}{\partial y}\frac{\partial F(x)}{\partial x} + \frac{\partial G(y)}{\partial y} + \frac{\partial F(x)}{\partial x} + 1$$

🤔 **Question**

How many terms will be in the gradient of the last layer with respect to the first layer when there are N layers?

💡 Answer

$$\frac{\partial z}{\partial x} = \prod_{i=1}^{N} \left(\frac{\partial F(x_i)}{\partial x_i} + x_i \right)$$

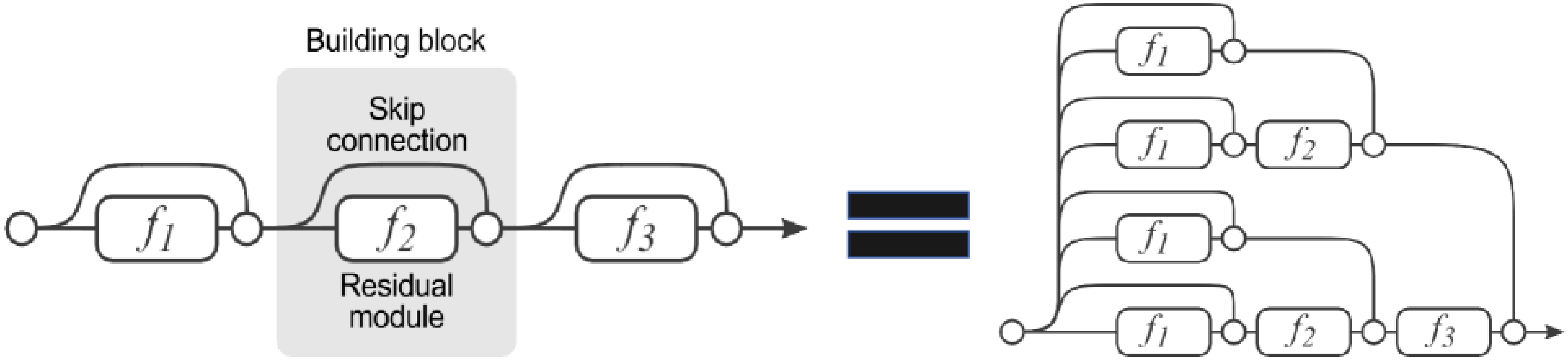
Thus, 2^N terms!

There are multiple paths for gradients to flow

$$\frac{\partial z}{\partial x} = \frac{\partial G(y)}{\partial y}\frac{\partial F(x)}{\partial x} + \frac{\partial G(y)}{\partial y} + \frac{\partial F(x)}{\partial x} + 1$$

And this solves the vanishing gradient problem... Why 🤔?

- Gradients can flow directly through the identity skip connections, bypassing layers in the residual path.
- Stronger gradient signals reach earlier layers more easily.
- (Bonus 🥳) **Ensemble Effect:** Stacking N blocks creates 2^N potential signal paths. This ensemble-like behavior smooths the loss landscape and reduces reliance on any single path.



(a) 3 residual blocks

(b) Unraveled view of (a)

Making Deep ResNets Practical: Bottleneck Blocks

For very deep networks (ResNet-50+), the basic 2-layer block becomes computationally expensive.

Solution: The Bottleneck Block (inspired by Inception)

1. **1x1 Conv: Reduces** channel dimensions (the "bottleneck").
2. **3x3 Conv** followed by 1x1 conv to restore channel dimension.
3. **Skip Connection:** Added as before (may need a projection if dimensions changed).

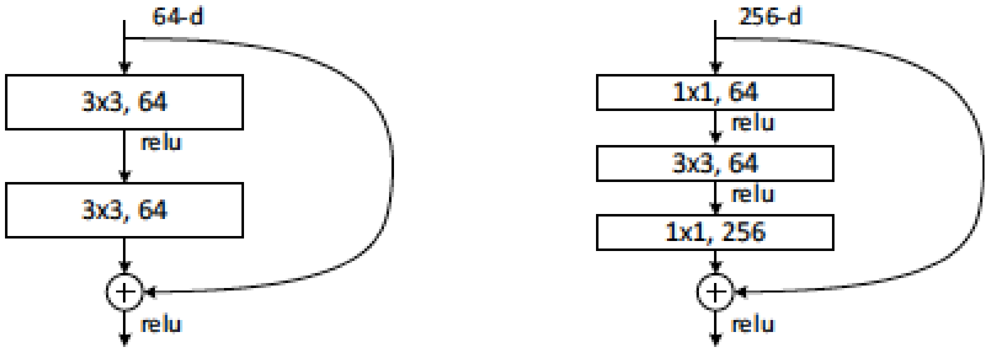


Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a "bottleneck" building block for ResNet-50/101/152.

Evolution: ResNeXt - Wider Residual Blocks ↔️

ResNeXt builds upon ResNet by exploring **cardinality** (the number of parallel pathways) within blocks:

- **Idea:** Instead of just making blocks deeper or wider (more channels), split the transformation into multiple parallel, lower-dimensional paths (using **grouped convolutions**).
- **Aggregate:** Sum the outputs of these parallel paths.
- **Result:** Increases model capacity and accuracy by adding *more paths* rather than just depth/width, often more parameter-efficiently.

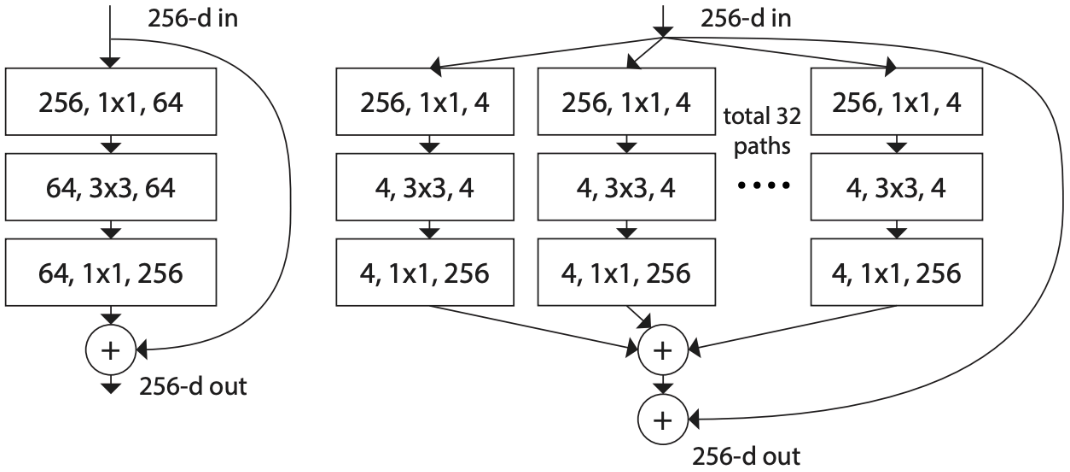


Figure 1. **Left**: A block of ResNet [14]. **Right**: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).

Impact and Legacy 🚀

- **Ubiquitous:** Residual connections are now a fundamental building block in deep learning.
- **Beyond CNNs:** Used extensively in Transformers (Attention is All You Need), U-Nets, AlphaFold, and many other state-of-the-art architectures.
- **Foundation:** ResNet's relative simplicity and effectiveness made it a powerful baseline and foundation for countless research projects and applications.

> ℹ️ **Note**
>
> The simplicity of adding a skip connection was key to its widespread adoption compared to more complex branched architectures.

Questions? / Exercises 💻

Suggested Exercises:

1. Implement a Basic Residual Block in PyTorch/TensorFlow.
2. Train a small ResNet (e.g., ResNet-18) on CIFAR-10 and compare to a plain CNN.
3. (Advanced) Implement Bottleneck blocks and build a deeper ResNet structure.

Thank You!

References 📚

- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR)*. [`ResNet`]
- Veit, A., Wilber, M. J., & Belongie, S. (2016). Residual networks behave like ensembles of relatively shallow networks. *Advances in neural information processing systems (NeurIPS)*. [`ResNet as Ensembles`]
- Xie, S., Girshick, R., Dollár, P., Tu, Z., & He, K. (2017). Aggregated residual transformations for deep neural networks. *Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR)*. [`ResNeXt`]
- *(Mention Szegedy et al. 2015/2016 if emphasizing Inception inspiration for bottlenecks)*