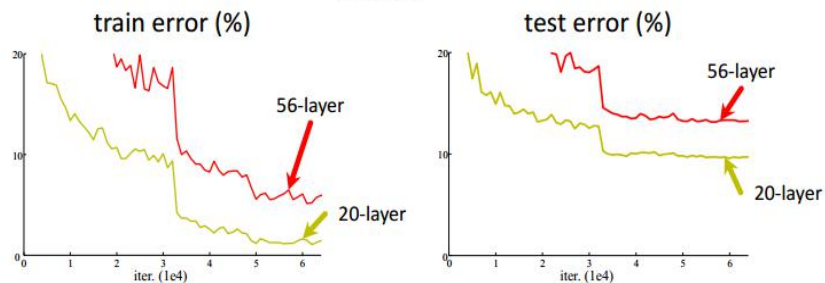


# Deep Residual Networks

SU  
2018/1116

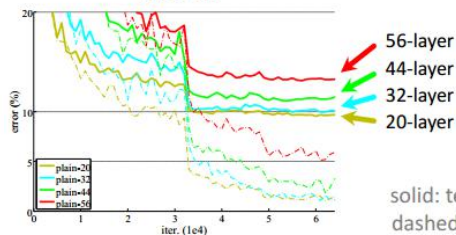
# Simply stacking layers?

CIFAR-10



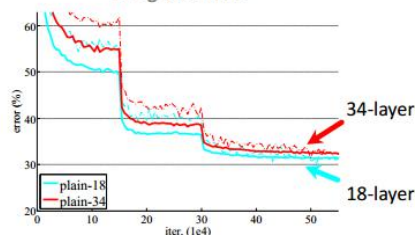
- Plain nets: stacking 3x3 conv layers...
- 56-layer net has **higher training error** and test error than 20-layer net

CIFAR-10



solid: test/val  
dashed: train

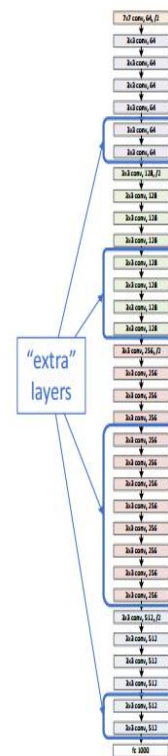
ImageNet-1000



a shallower model  
(18 layers)



a deeper counterpart  
(34 layers)

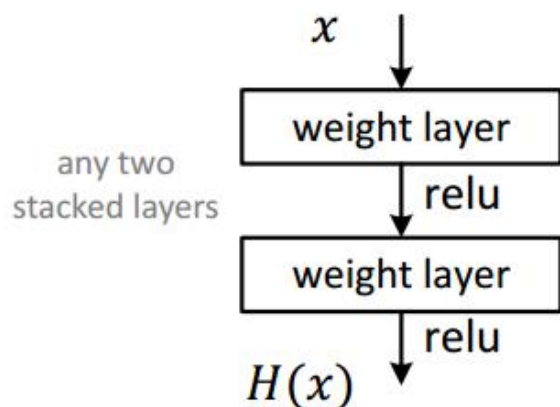


- A deeper model should not have **higher training error**
- A solution *by construction*:
  - original layers: copied from a learned shallower model
  - extra layers: set as **identity**
  - at least the same training error
- **Optimization difficulties**: solvers cannot find the solution when going deeper...

- “Overly deep” plain nets have **higher training error**
- A general phenomenon, observed in many datasets

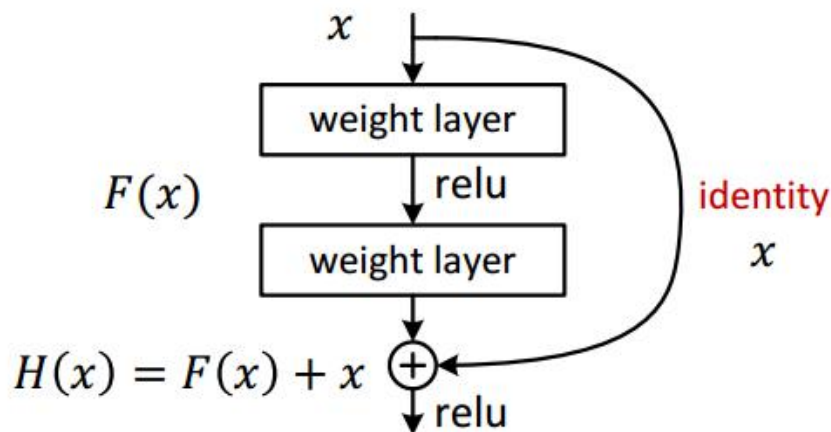
# Deep Residual Learning

- Plain net



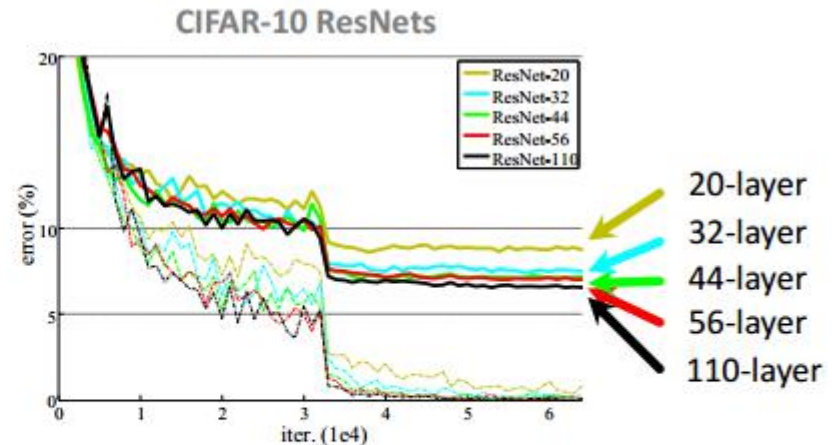
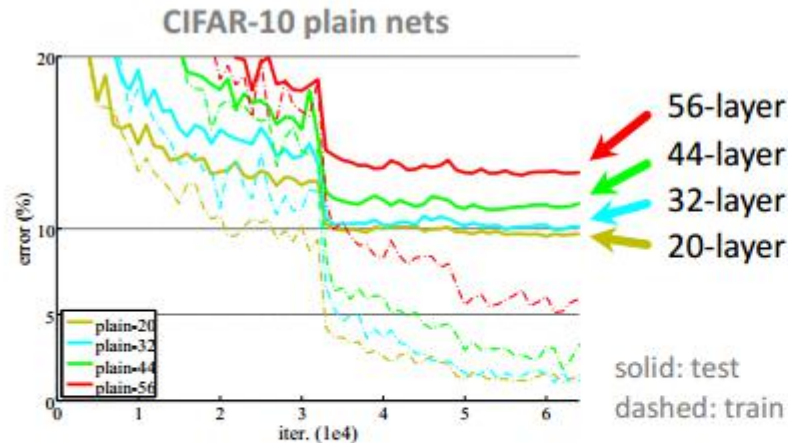
$H(x)$  is any desired mapping,  
hope the 2 weight layers fit  $H(x)$

- **Residual** net



$H(x)$  is any desired mapping,  
~~hope the 2 weight layers fit  $H(x)$~~   
hope the 2 weight layers fit  $F(x)$   
let  $H(x) = F(x) + x$

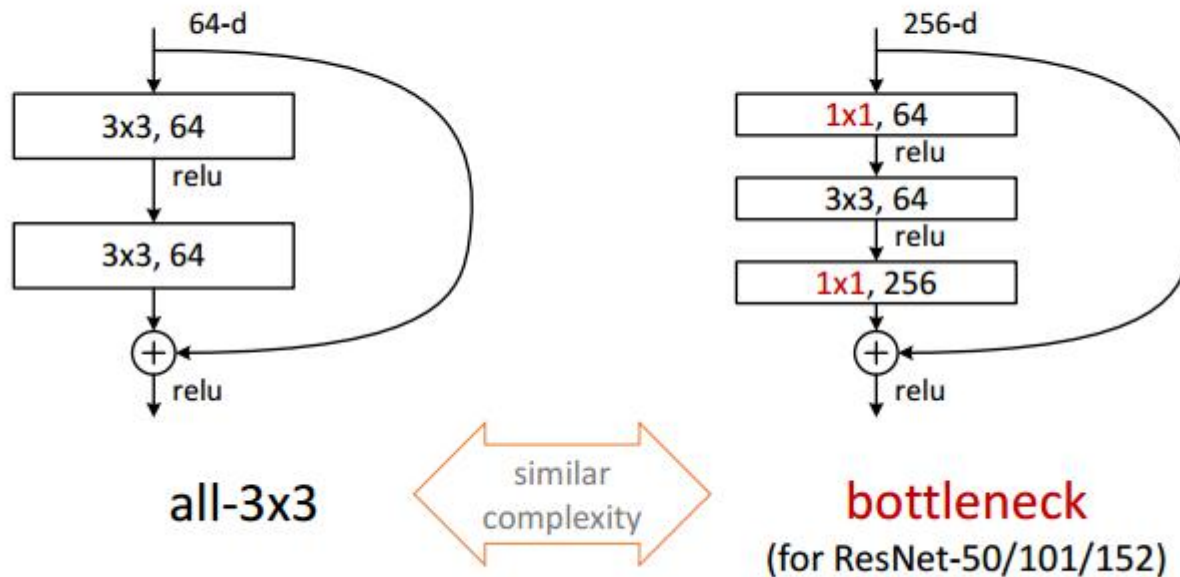
# Result on CIFAR-10



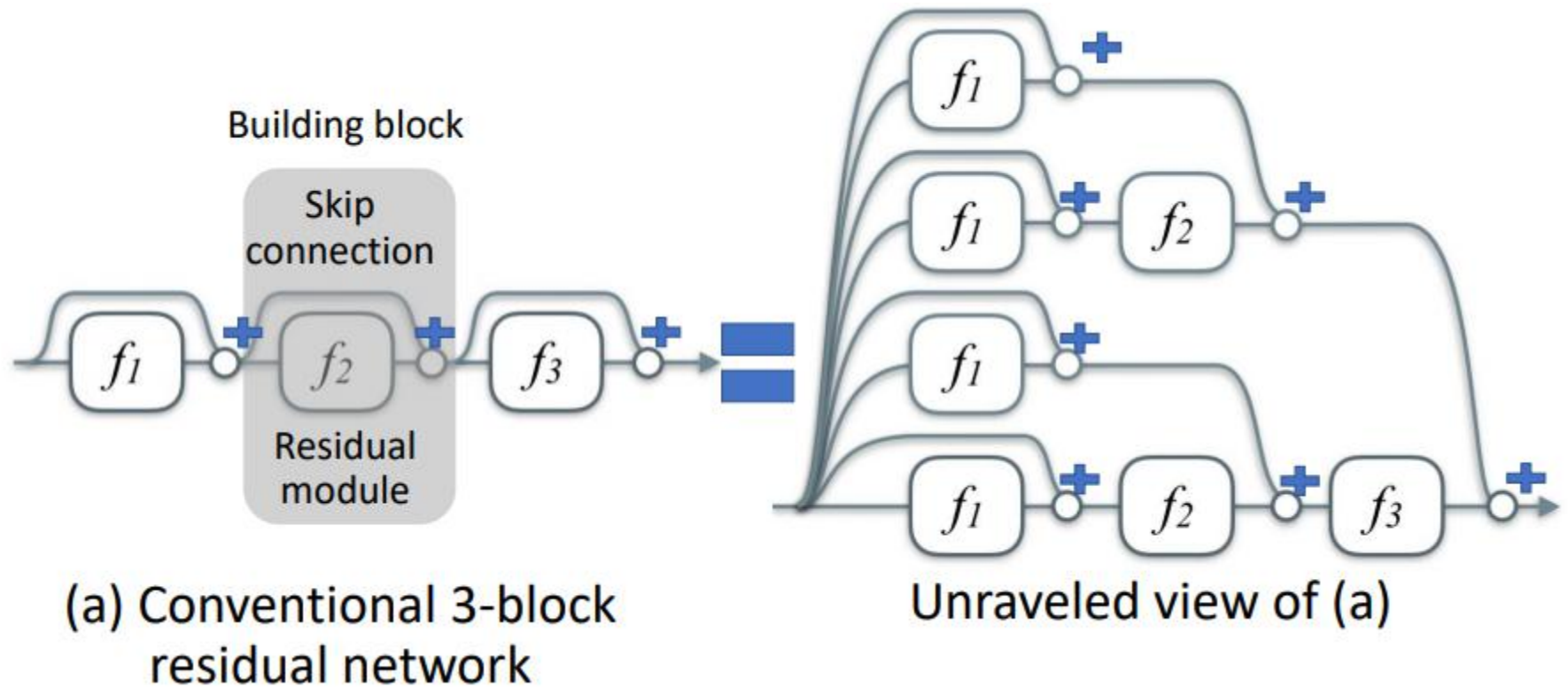
- Deep ResNets can be trained without difficulties
- Deeper ResNets have **lower training error**, and also lower test error

# ImageNet experiments

- A practical design of going deeper

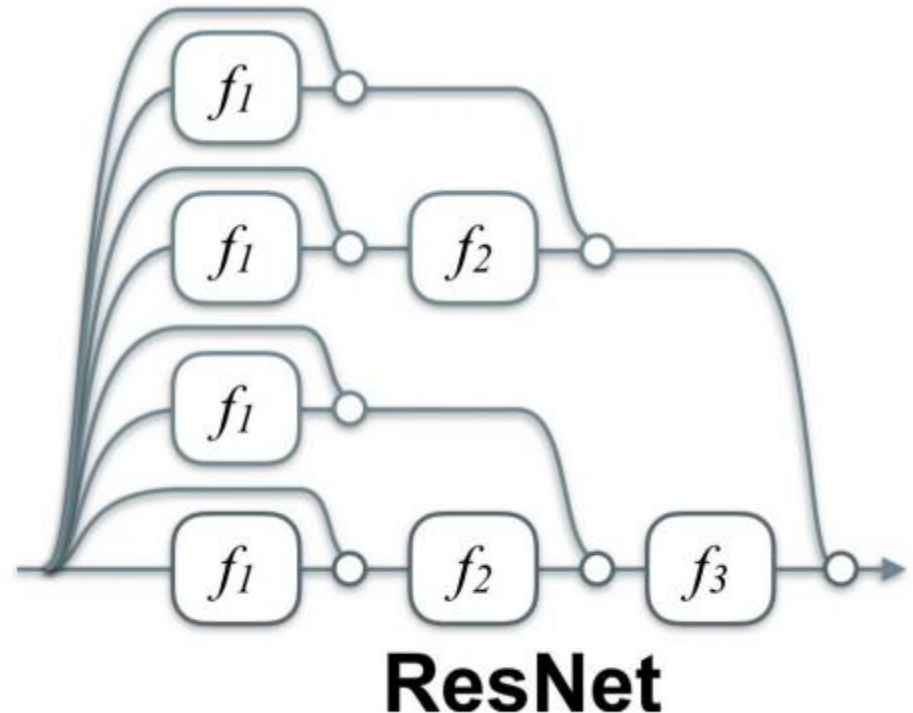


# Why does this work?



# Why does this work?

The unraveled view is equivalent and showcases the many paths in ResNet.



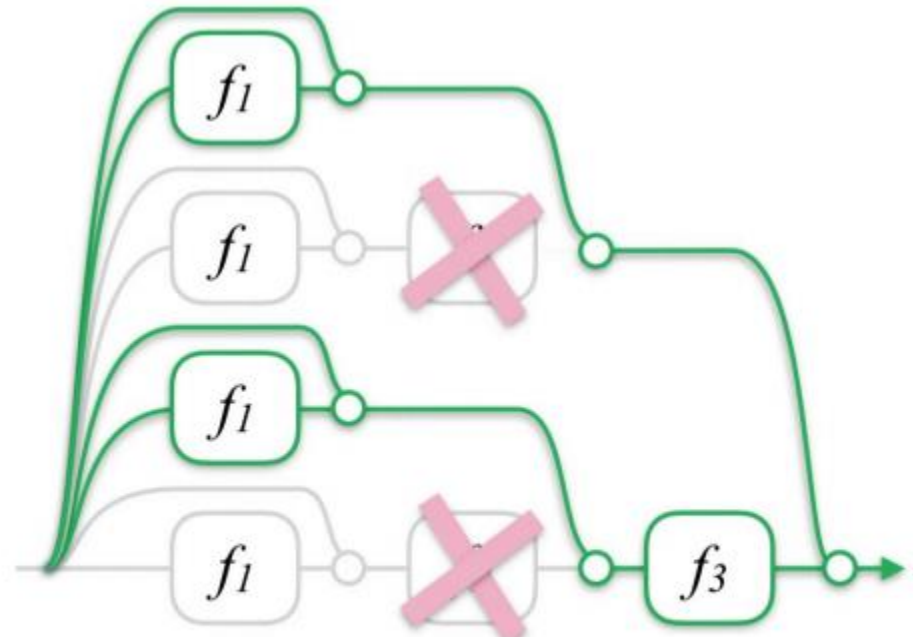


# Deletion of one layer at test time



**VGG**

All paths are affected

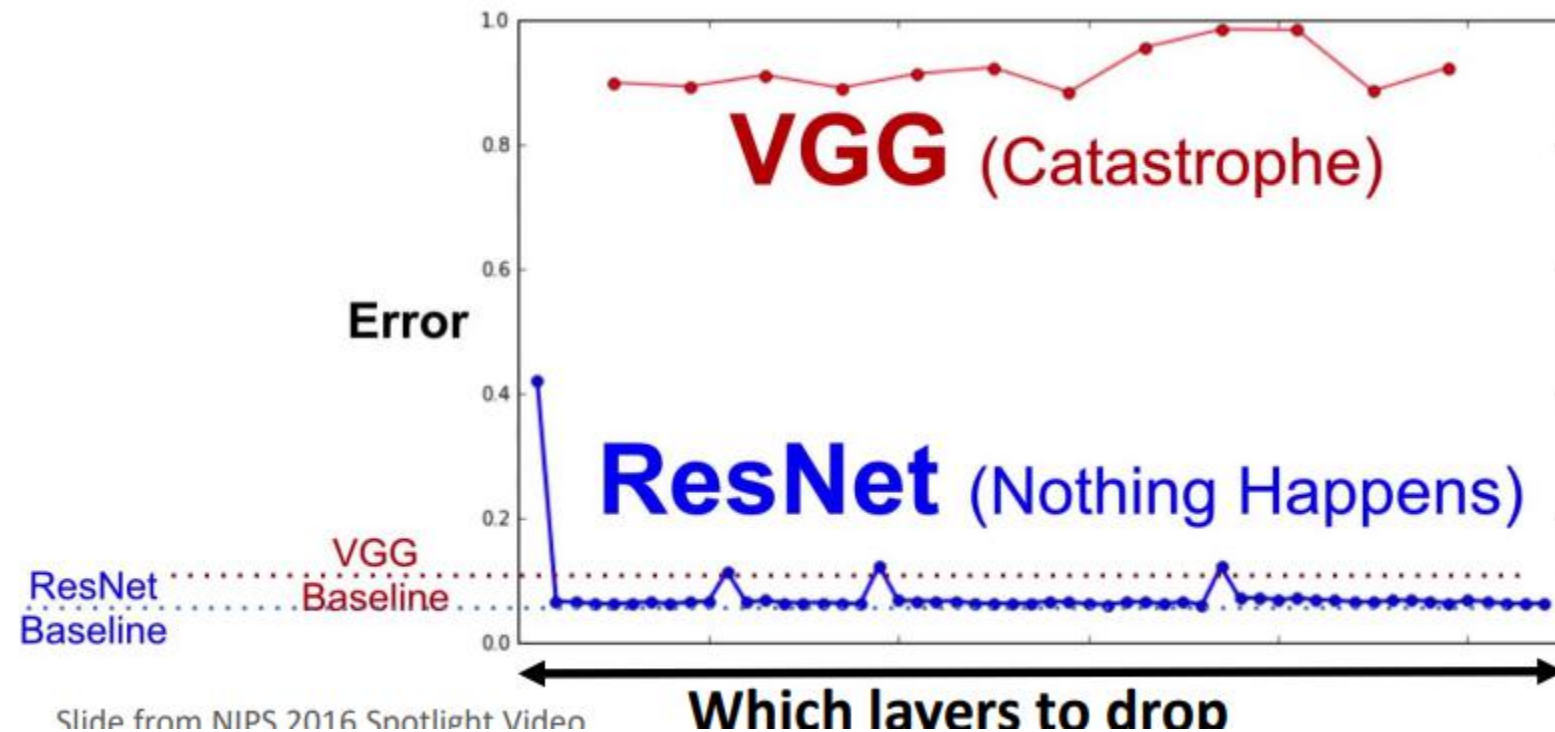


**ResNet**

Only **half** of the paths are affected

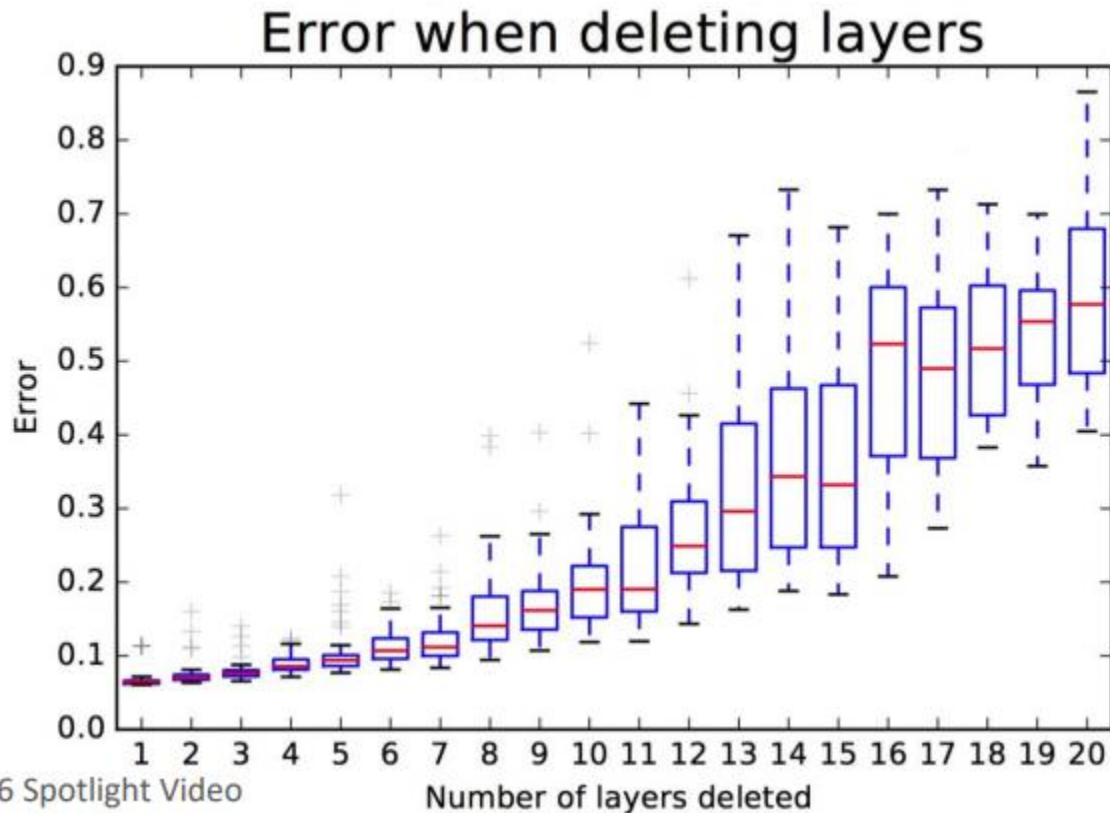


# Deletion of one layer at test time



Slide from NIPS 2016 Spotlight Video

# Deletion of several layers



Slide from NIPS 2016 Spotlight Video

# Conclusion 1

- Residual Networks consist of many paths.
- Although trained jointly, they do not strongly depend on each other: Ensemble-like behavior

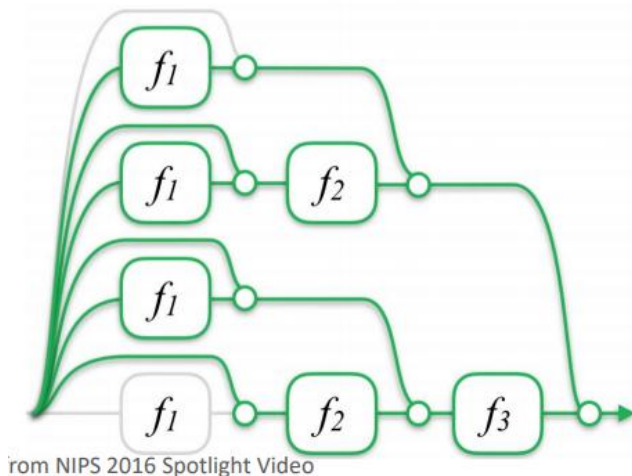
# Path Length

Distribution of path length

There are very few **short paths...**

And very few **long paths...**

Most paths are **medium length!**



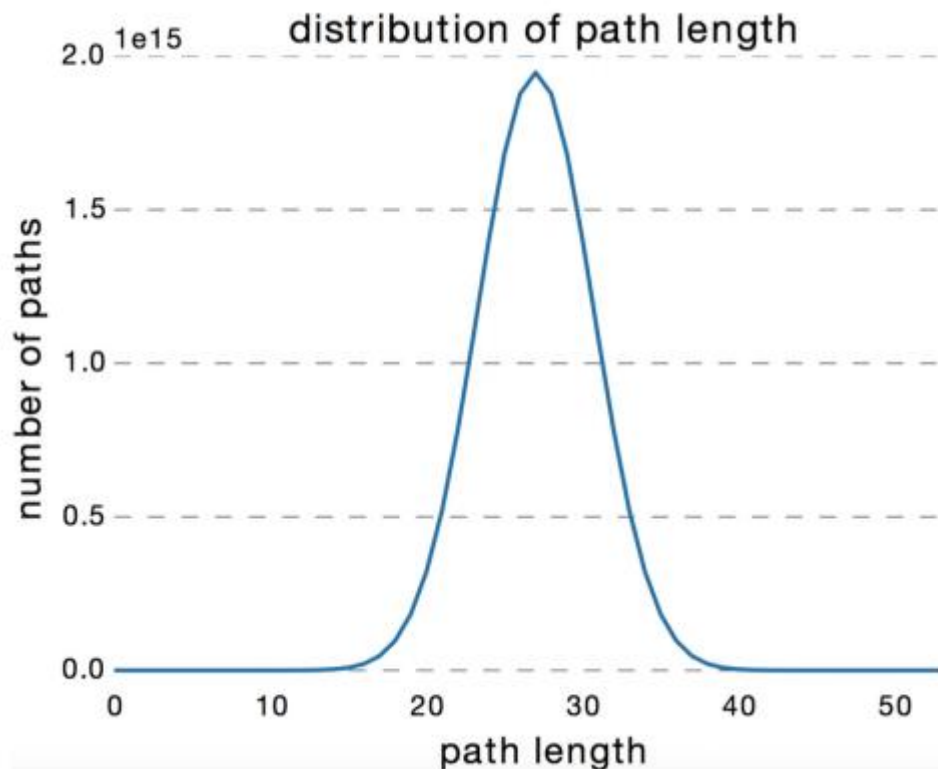
**Residual networks  
contain many paths.**

Previous networks have a  
single path.

**Only short paths  
contribute gradient  
during training.**

Vanishing gradient suppresses  
gradient from long paths.

# Distribution of path length



There are very few **short paths...**

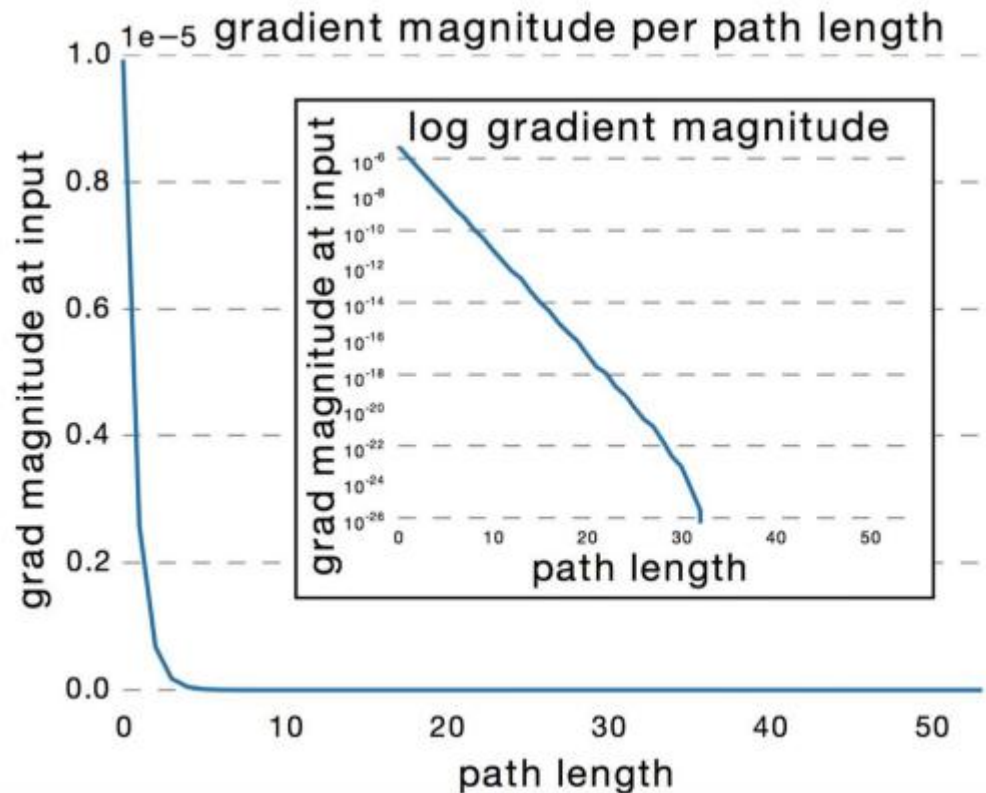
And very few **long paths...**

Most paths are **medium length!**

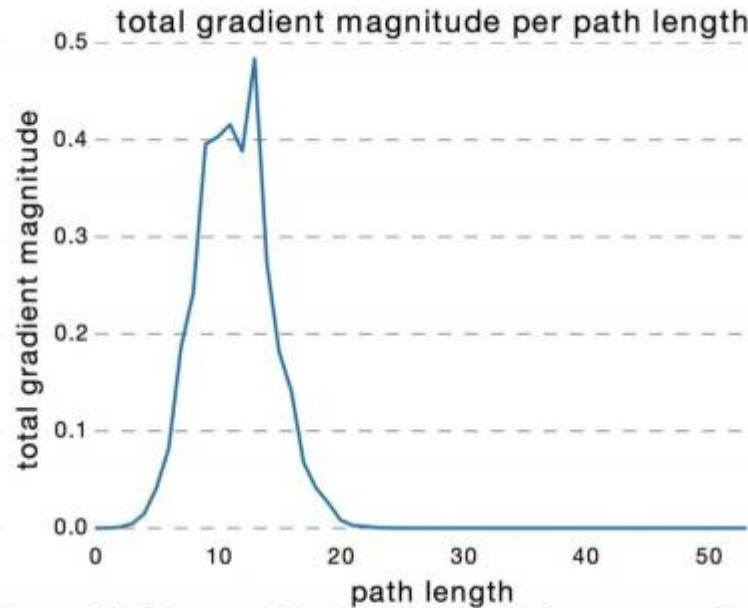
Paths length follows a **binomial distribution.**

# Vanishing gradient

The gradient magnitude **decreases exponentially** with increasing path length.



# Gradient during training with path length



Combining the path length distribution and the vanishing gradients, one can observe that most of the gradient comes from relatively short paths.



# Conclusion 2

- Residual Networks consist of many paths.
- Although trained jointly, they do not strongly depend on each other: Ensemble-like behavior
- Most paths through a ResNet are relatively short.
- During training, gradients only flow through short paths.

## Reference:

- Residual Networks Behave Like Ensembles of Relatively Shallow Networks
- Deep Residual Learning for Image Recognition