Week 5: Convolutional Neural Networks - 2

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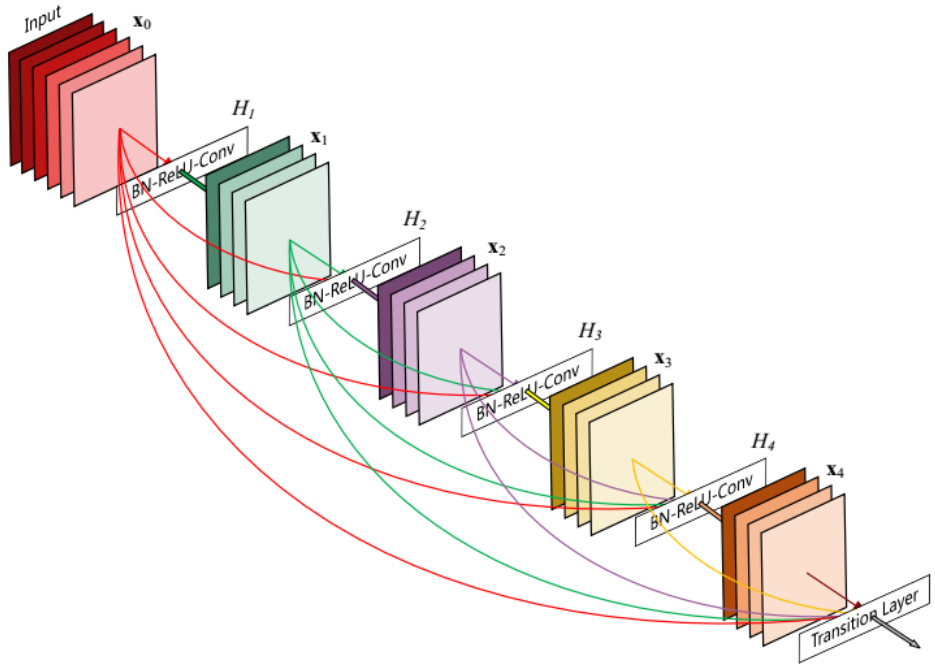
From ResNets to DenseNets

- DenseNet: connect all layers directly with each other

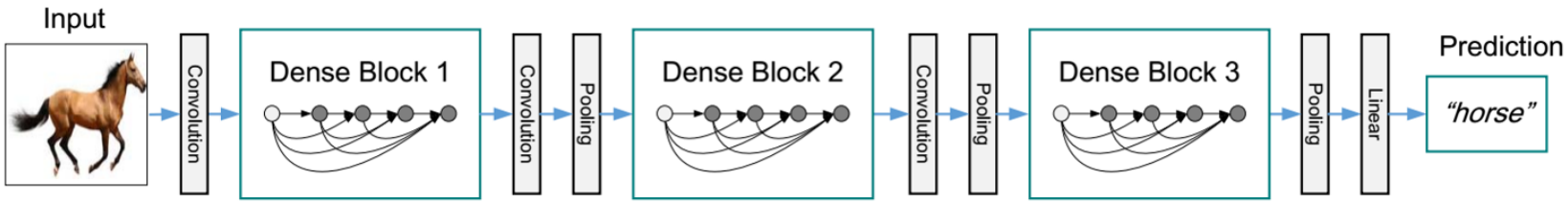


- Differ from Resnet: not sum, but **concatenate** feature maps
- Encourages **feature reuse** throughout the network
- Can ensure maximum information flow between layers

figure from Huang, Liu, van der Maaten, Weinberger, "Densely connected convolutional networks", CVPR 2017

DenseNets

- Use transition layers to change size of feature maps



- Training: easily back-propagate errors via skip connections
- Each layer can have fewer (e.g., 12) kernels, and still sufficient to obtain state-of-the-art results
- Reason: each layer has access to all preceding feature-maps in its block, and therefore to the network's 'collective knowledge'

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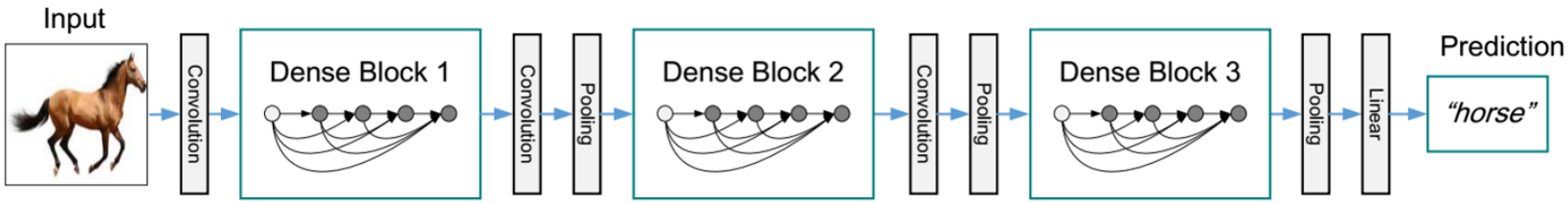

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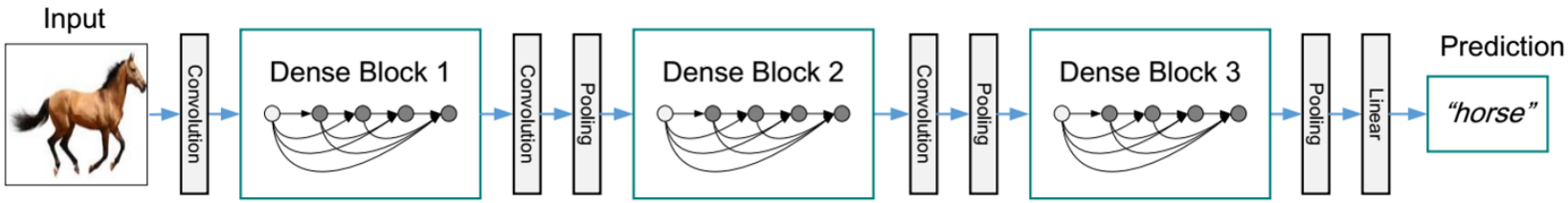

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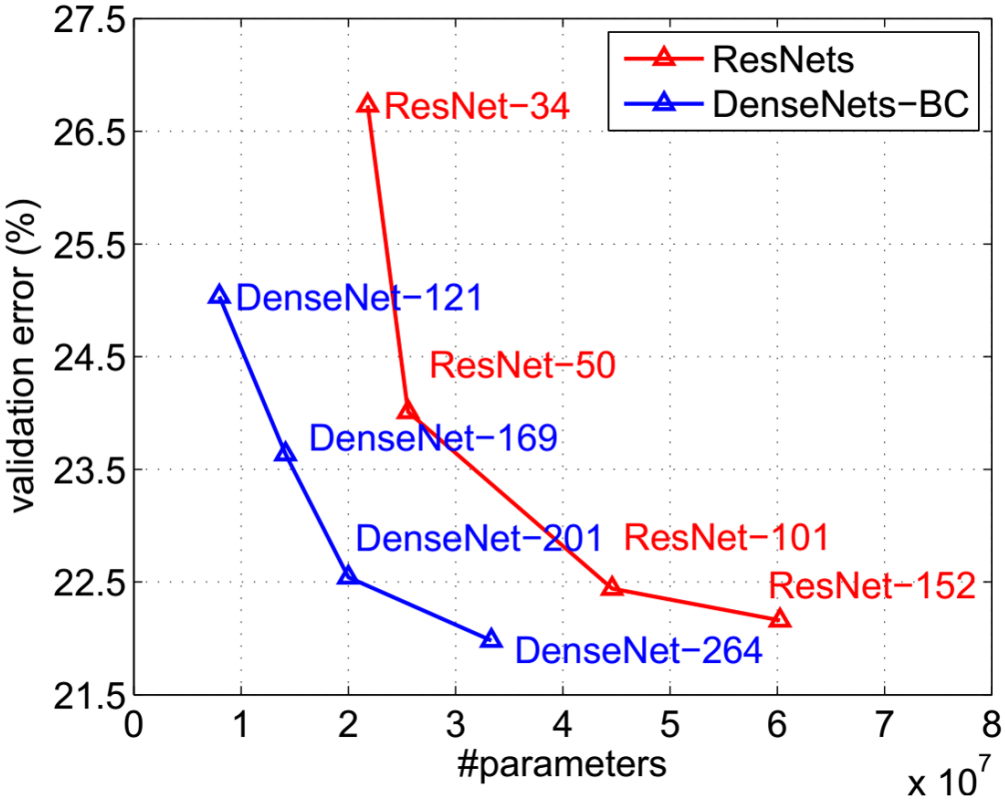
DenseNets (cont')

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201
Convolution	112×112	7×7 conv, stride 2		
Pooling	56×56	3×3 max pool, stride 2		
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56	1×1 conv		
	28×28	2×2 average pool, stride 2		
Dense Block (2)	28×28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28	1×1 conv		
	14×14	2×2 average pool, stride 2		
Dense Block (3)	14×14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$
Transition Layer (3)	14×14	1×1 conv		
	7×7	2×2 average pool, stride 2		
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$
Classification Layer	1×1	7×7 global average pool		
		1000D fully-connected, softmax		

- Tens of conv layers per dense block
- Use 1×1 conv layer to reduce number of feature maps

DenseNets (cont')



- Fewer parameters (and computation) for similar performance
- Less prone to overfitting (due to fewer parameters)

More ResNet variations

Sometimes, we may think differently for innovation!

More ResNet variations

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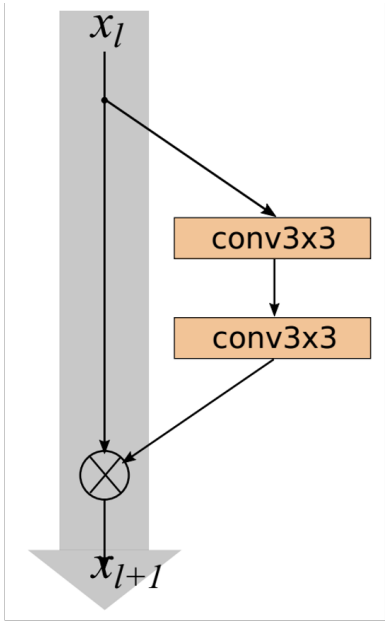
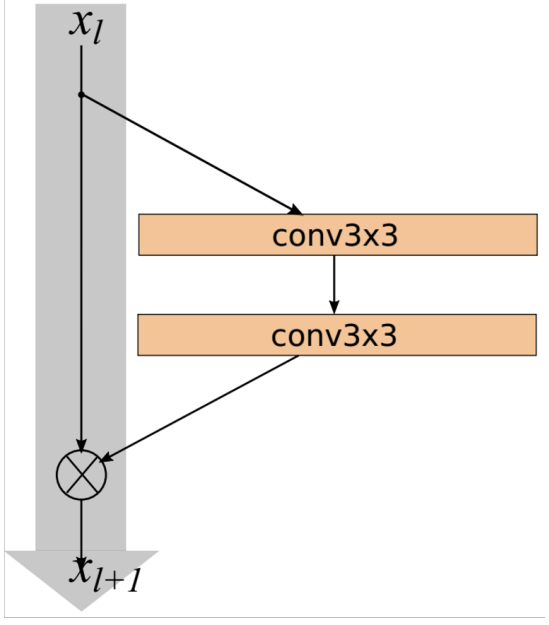
How about not making network deeper, but wider?

Wide ResNet



Basic ResNet layer

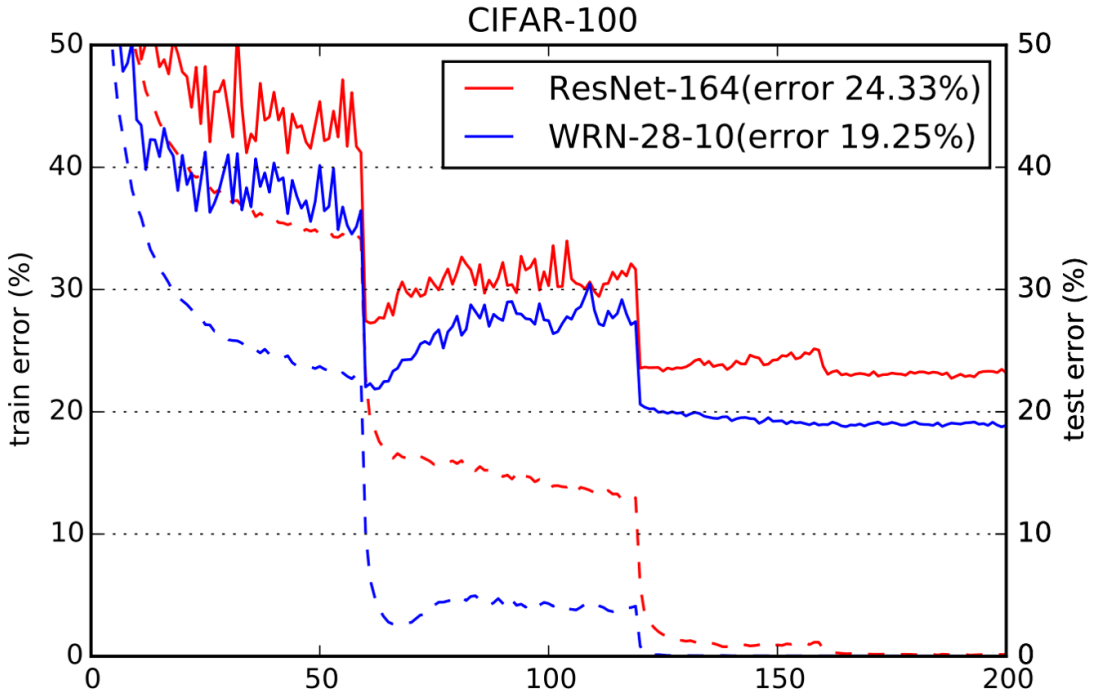


Wide ResNet layer

- Wide Resnet: more kernels in each layer, with fewer layers

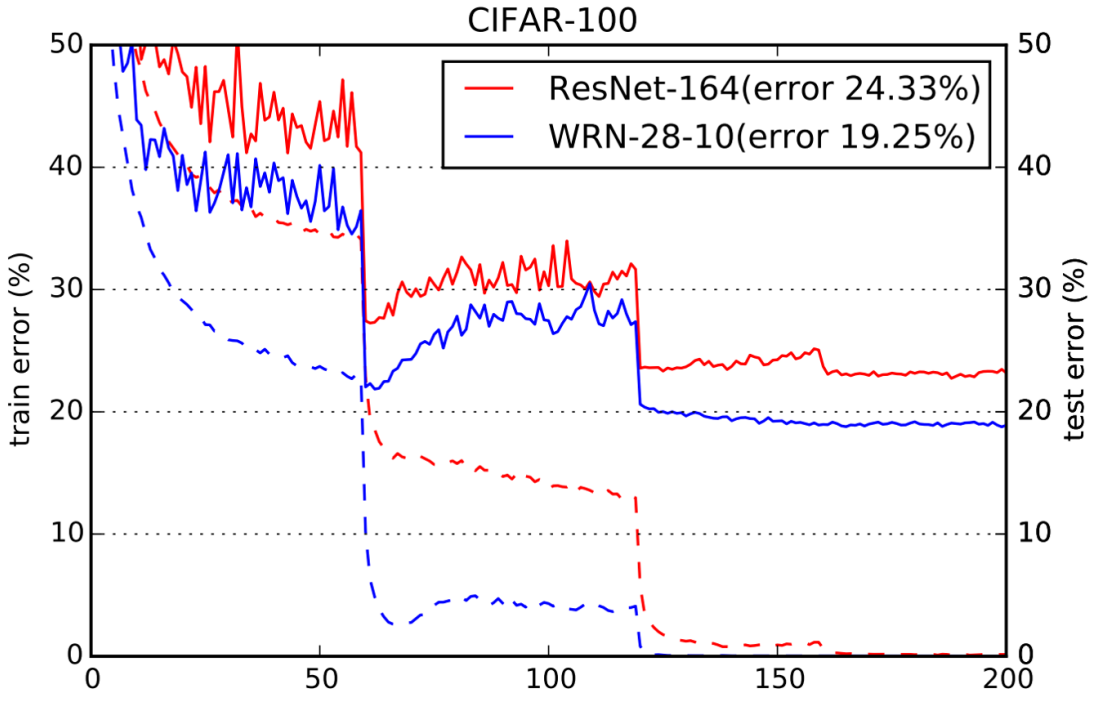
figure from Zagoruyko, Komodakis, "Wide residual networks", BMVC 2016

Wide ResNet (cont')



- 'WRN-28-10': 28 conv layers, 10 times original kernel number
- Widening improves performance
- So, ResNet works not due to extreme depth: 'skip connection'

Wide ResNet (cont')



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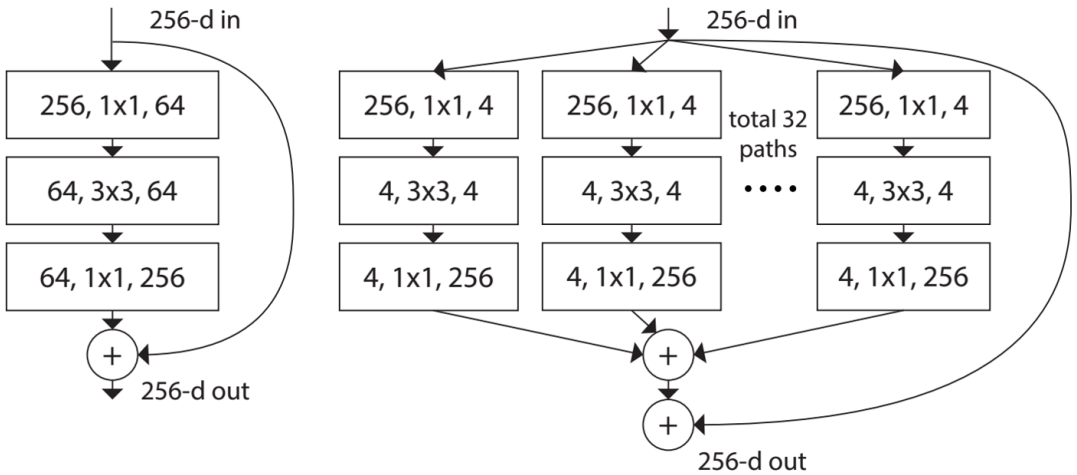
More ResNet variations

Besides deeper and wider networks ...

ResNeXt: besides deeper and wider

- ResNeXt: divide ResNet block into smaller transformations, then aggregate.

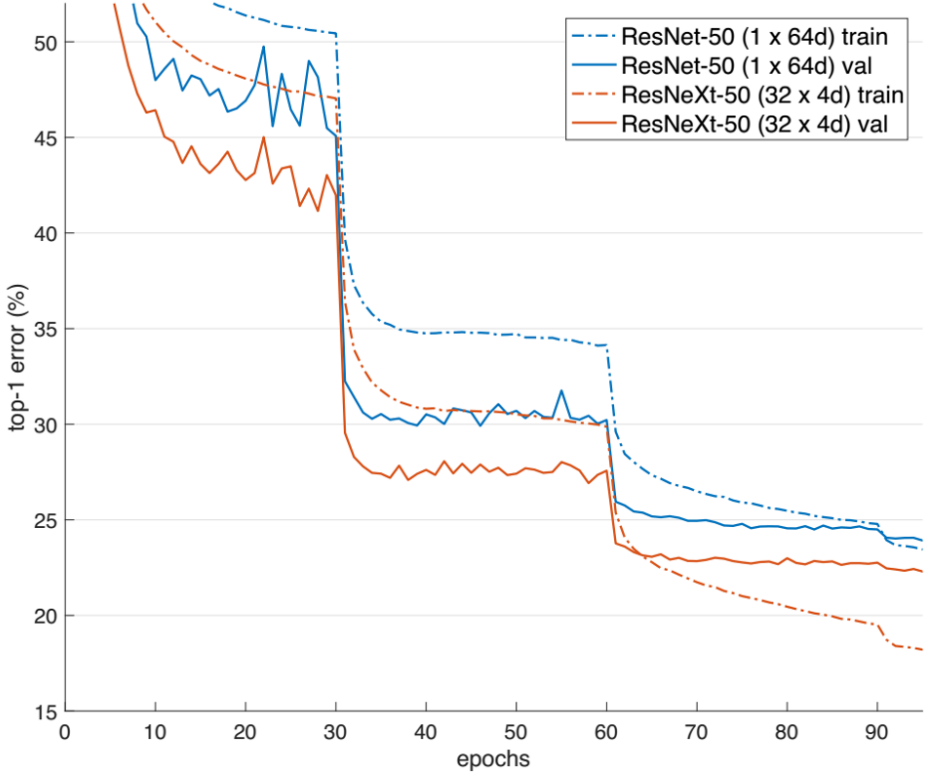


- Left: ResNet block; Right:ResNeXt block with **cardinality** 32
- Each layer: (# input channels, filter size, # output channels)
- Two blocks have similar number of parameters

Figures and tables from Xie, Girshick, Dollar, Tu, He, "Aggregated residual transformations for deep neural networks", CVPR 2017

ResNeXt (cont')

- Comparison on ImageNet-1K dataset



- ResNeXt performs better than ResNet, with similar complexity
- Lower training error indicates more powerful feature learning

ResNeXt (cont')

- Comparison on ImageNet-1K dataset

	setting	top-1 err (%)	top-5 err (%)
1× complexity references:			
ResNet-101	1 × 64d	22.0	6.0
ResNeXt-101	32 × 4d	21.2	5.6
2× complexity models follow:			
ResNet-**200** [14]	1 × 64d	21.7	5.8
ResNet-101, wider	1 × **100**d	21.3	5.7
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- Increasing cardinality is better than increasing depth and width

ResNeXt (cont')

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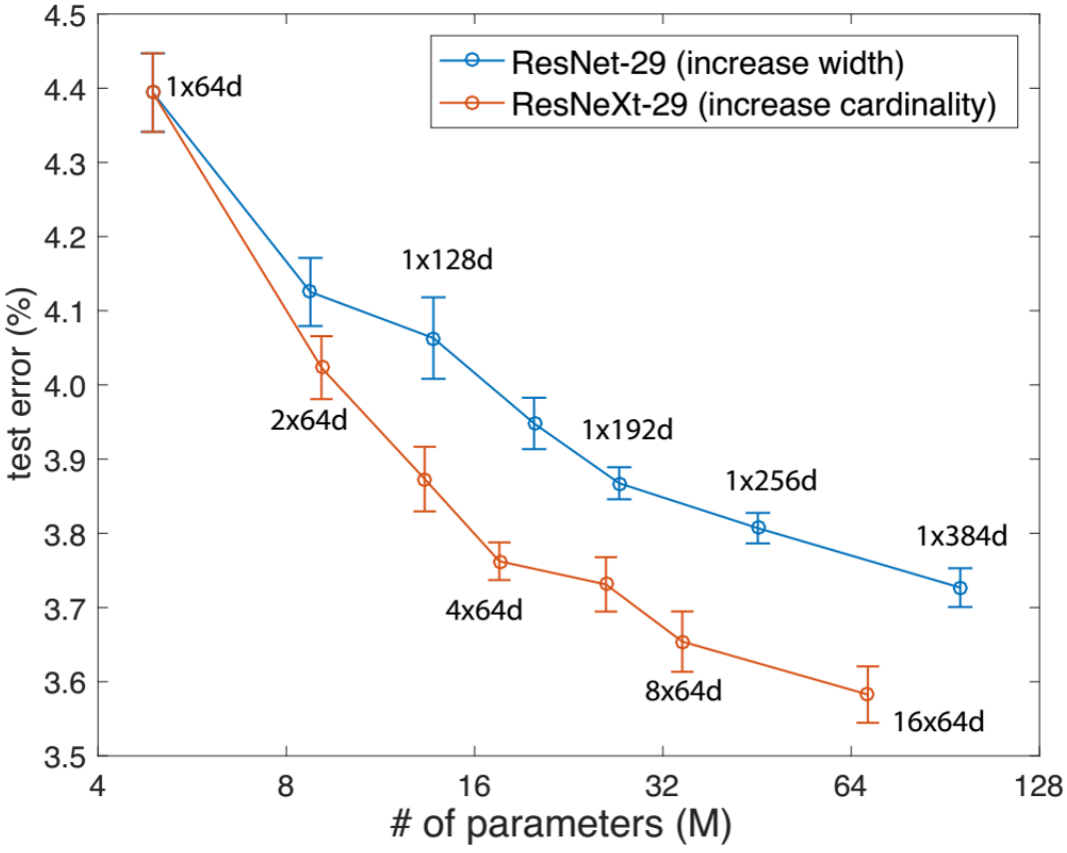
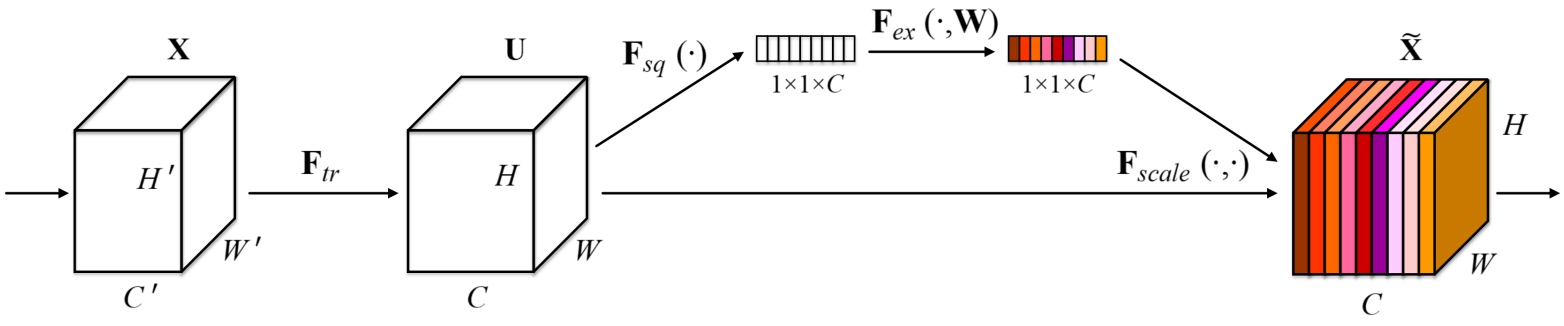
ResNeXt (cont')

- Comparison on CIFAR-10 dataset

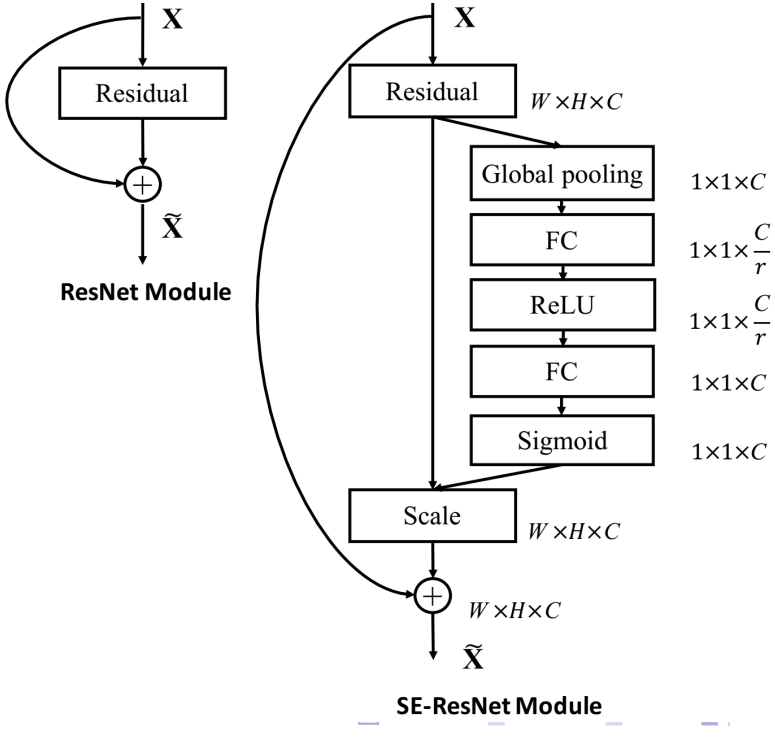


- Again: increasing cardinality is more effective than width

SENet: Squeeze-and-Excitation Networks



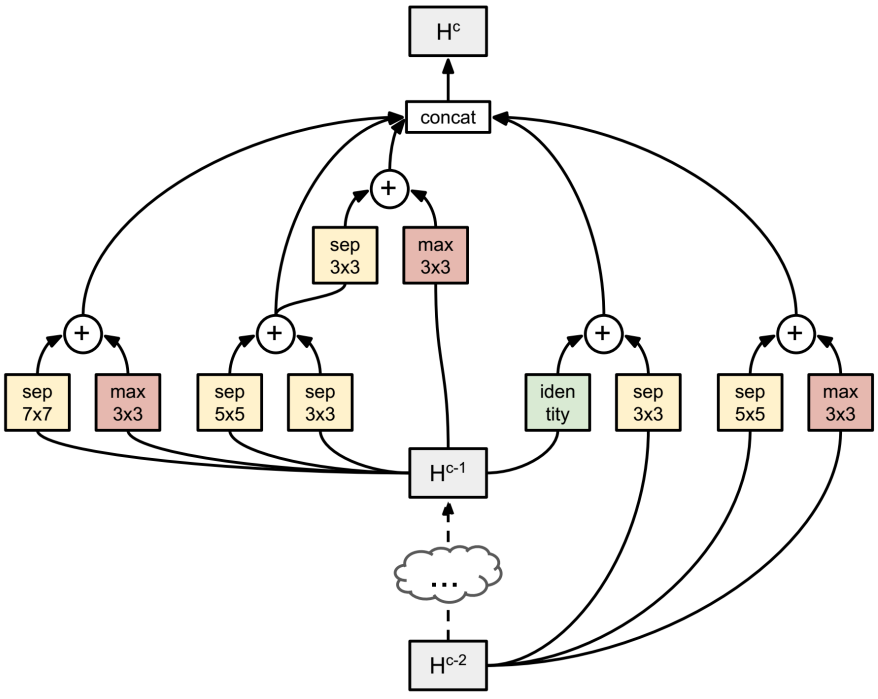
- model channel dependencies
- control channel excitation
- plug-in operator
- SENet = SE-ResNeXt152
- won 2017 ImageNet contest, with 2.25% top-5 error

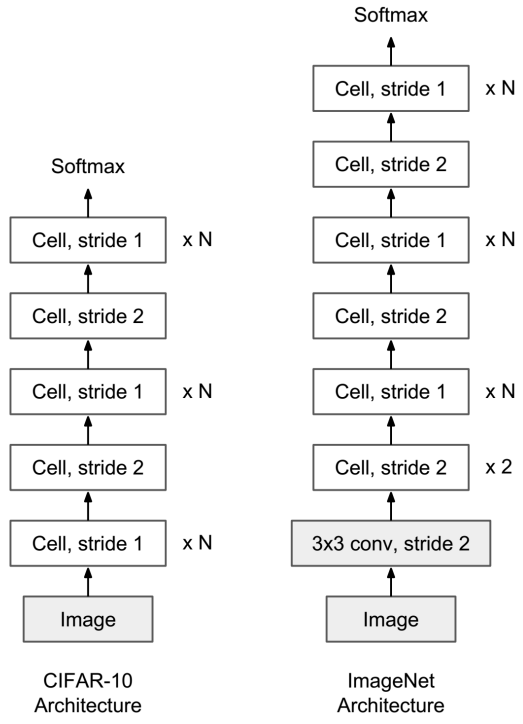


Figures from Hu, Shen, Sun, "Squeeze-and-Excitation Networks", CVPR 2018

PNASNet: progressive neural architecture search

- All model architectures above are designed by humans.
- Recently: AutoML techniques for neural architecture search





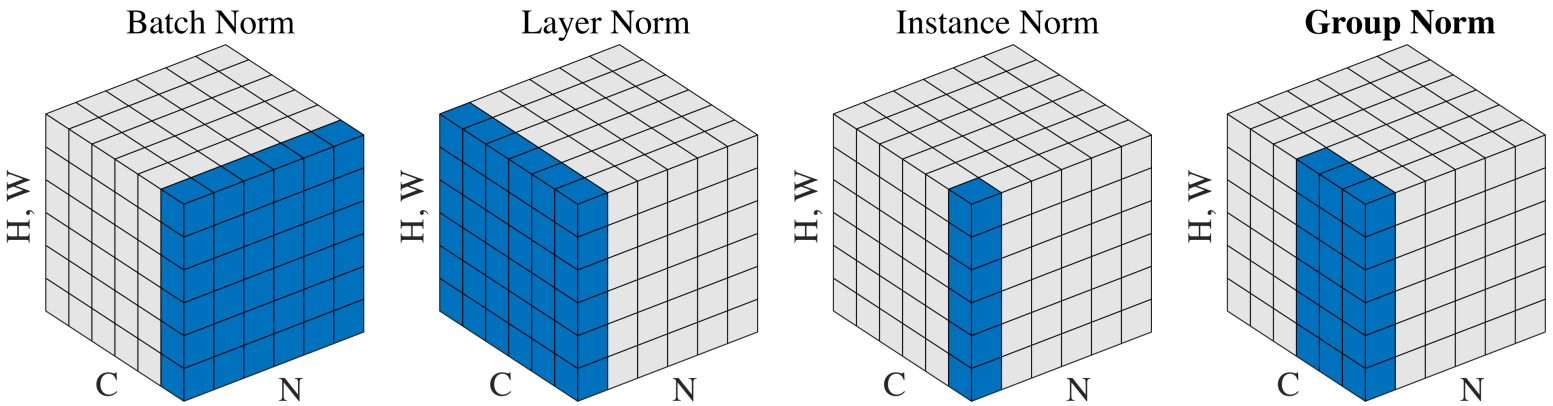
Note: 'sep' for 'depthwise separable convolution'

- PNASNet outperforms almost all hand-crafted models

Figures from Liu, Zoph, Neumann, Shlens, Hua, Li, Fei-Fei, Yuille, Huang, Murphy, "Progressive Neural Architecture Search", ECCV 2018

Before Next...Group Normalization

- Batch normalization not work well for small batch size
- Group normalization (GN): divide channels into groups, then normalize within each group; works for single data.



Note (in rightmost figure): 2 groups, 3 channels per group

- Layer Norm (LN) and Instance Norm (IN) are special GNs
- LN and IN not work well for visual recognition tasks

Figure from Wu, He, "Group normalization", ECCV 2018

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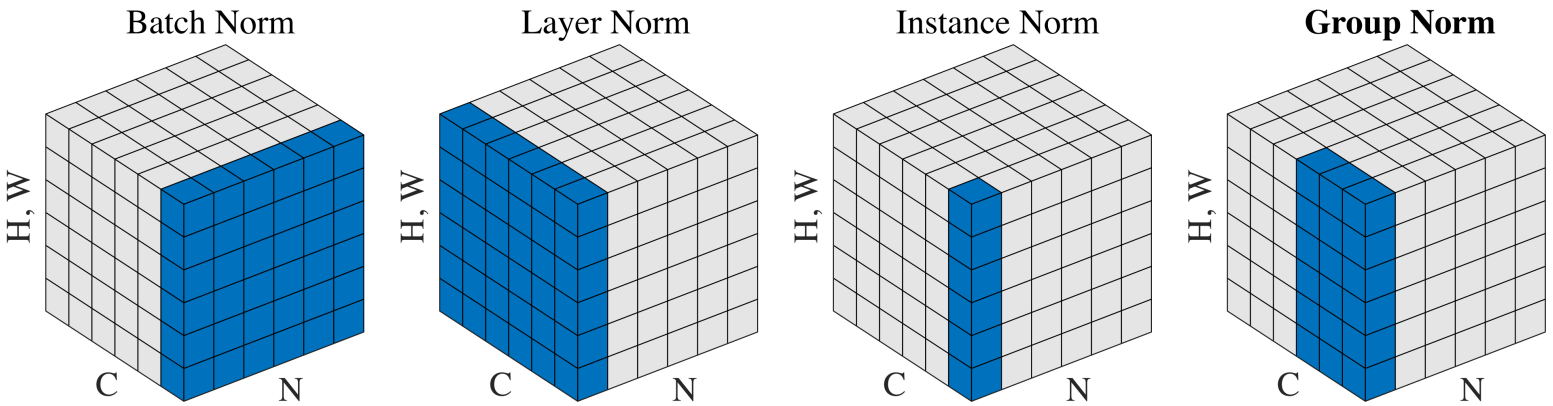

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Next...

Let's see a few applications of CNN models!

Face verification or identification

- How do you recognize whose face it is?

Who is this?

Dataset ($>10^6$) with IDs

Face verification or identification

- How do you recognize whose face it is?

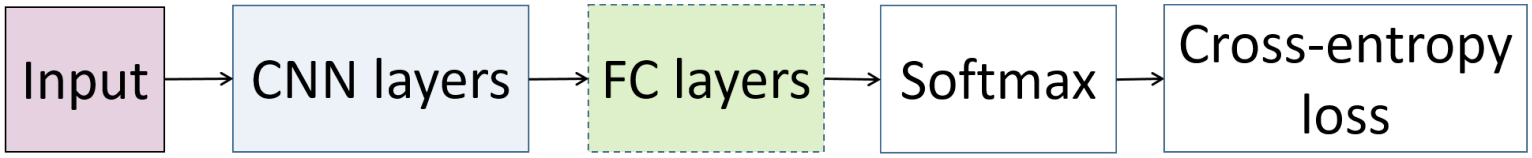
Who is this?

Dataset ($>10^6$) with IDs

- Probably: compare this face with many familiar faces in brain

Face verification (cont')

- Consider it as an image classification problem?



- Issue 1: not comparing face similarity/distance directly
- Issue 2: too many parameters to learn
  e.g. for last layer: 100 features * 1,000,000 classes
- Issue 3: difficult to collect many faces per person
- Instead: FaceNet

Face verification (cont')

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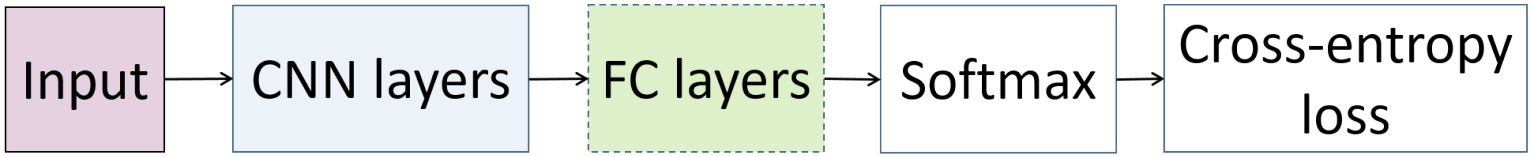

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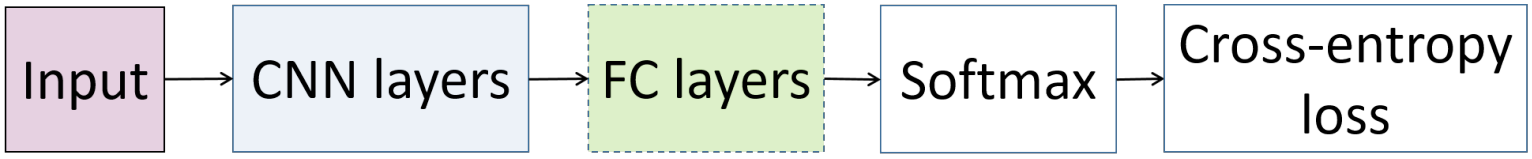

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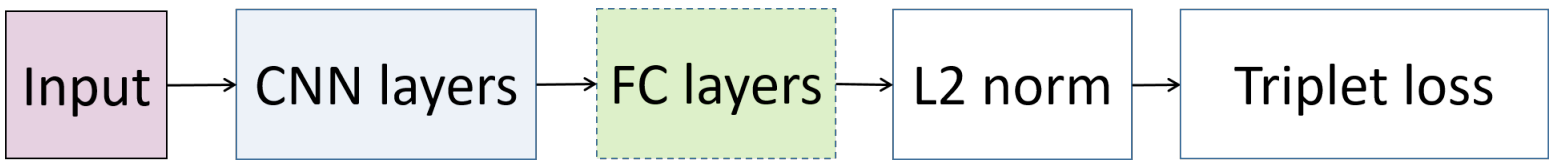

FaceNet for face verification

- FaceNet: a convolutoinal network to transform images into a low-dimensional (i.e., 128) feature space in which face images of same identity are closer than images of different identities.

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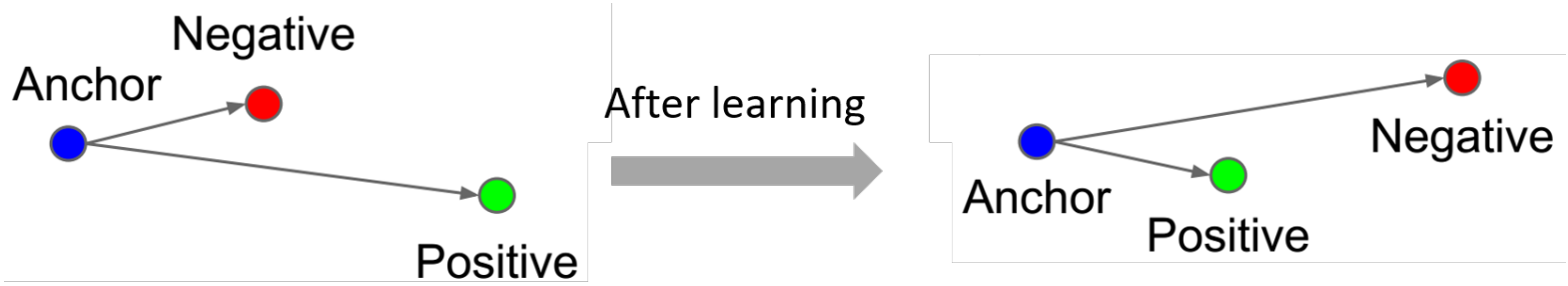

(Image space) (feature space)

- 'anchor' and 'positive' images have same identity
- 'anchor' and 'negative' images have different identity

Figure here and evaluation results below from Schroff, Kalenichenko, Philbin, "FaceNet: a unified embedding for face recognition and clustering", CVPR 2015

Triplet loss for FaceNet

- To ensure that an image $\mathbf{x}_i^a$ (anchor) is closer to every other images $\mathbf{x}_i^p$ (positive) of the same person than to any image $\mathbf{x}_i^n$ of any other person, we hope

$$\|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^p)\|^2 + \alpha \quad < \quad \|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^n)\|^2$$
$$\forall\ (\mathbf{x}_i^a, \mathbf{x}_i^p, \mathbf{x}_i^n) \in \mathcal{T}$$

  $\mathcal{T}$: training triplets $\{(\mathbf{x}_i^a, \mathbf{x}_i^p, \mathbf{x}_i^n)\}_{i=1}^N$; α: positive constant
  $\mathbf{f}(\cdot)$: feature representation of input via CNN model

- So, the loss over one triplet $(\mathbf{x}_i^a, \mathbf{x}_i^p, \mathbf{x}_i^n)$ can be designed as

$$l(\mathbf{x}_i^a, \mathbf{x}_i^p, \mathbf{x}_i^n) = \begin{cases} 0, & \\ \quad \text{if } \|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^p)\|^2 + \alpha < \|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^n)\|^2 & \\ \|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^p)\|^2 + \alpha - \|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^n)\|^2, & \\ \quad \text{if } \|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^p)\|^2 + \alpha \geq \|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^n)\|^2 & \end{cases}$$

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Triplet loss for FaceNet (cont')

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- Triplet loss: on the whole training dataset

$$L(\boldsymbol{\theta}) = \sum_{i=1}^{N} \left[\|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^p)\|^2 + \alpha - \|\mathbf{f}(\mathbf{x}_i^a) - \mathbf{f}(\mathbf{x}_i^n)\|^2\right]_+$$

$\boldsymbol{\theta}$: model parameters

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- Output of FaceNet is not a class label or probability, but a 128-dim feature vector $\mathbf{f}(\mathbf{x})$

FaceNet: evaluation

- Training set generation: select 'hard' triplets which have larger triplet loss!
- CNN models: VGG-like or GoogleNet, $15 \sim 22$ layers

- LFW dataset: Labelled Faces in the Wild
  13233 images; 5749 people; 1680 people with ≥ 2 images
- In training: used other labelled data set.
- Verification rule: given two face images $\mathbf{x}_i$ and $\mathbf{x}_j$, if $\|\mathbf{f}(\mathbf{x}_i) - \mathbf{f}(\mathbf{x}_j)\|^2 < \tau$, then $\mathbf{x}_i$ and $\mathbf{x}_j$ are considered 'same'.
- Threshold $\tau = 1.24 \sim 1.26$ was experimentally decided

- Verification accuracy: $99.63\% \pm 0.09\%$, better than humans!

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FaceNet: evaluation (cont')

- Do you think each pair is from same person?

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- Do you think each pair is from same person?

FaceNet: evaluation (cont')

- Do you think each pair is from same person?

- Each pair is from different persons
- previous page: each pair from same person

FaceNet: evaluation (cont')

- Do you think each pair is from same person?

- Each pair is from different persons
- previous page: each pair from same person
- These pairs are ALL the mistakes made by FaceNet!

Style transfer

- Generate a new image $\mathbf{x}$ which has style of image $\mathbf{a}$ and content of image $\mathbf{p}$

Style image $\mathbf{a}$

Content image $\mathbf{p}$

Style transfer

Style-transferred image $\mathbf{x}$

Pictures from https://harishnarayanan.org/writing/artistic-style-transfer/

Style transfer: loss function

- Idea: design and minimize a loss function

$$\mathcal{L}(\mathbf{x}; \mathbf{a}, \mathbf{p}, \boldsymbol{\theta}) \quad = \quad \mathcal{L}_{content}(\mathbf{p}, \mathbf{x}) + \lambda \mathcal{L}_{style}(\mathbf{a}, \mathbf{x})$$

such that

$$\mathcal{L}_{\text{content}}\left(\text{  }, \text{  } \right) \approx 0$$

$$\mathcal{L}_{\text{style}}\left(\text{  }, \text{  } \right) \approx 0$$

- To be optimized is not CNN parameters, but input image $\mathbf{x}$

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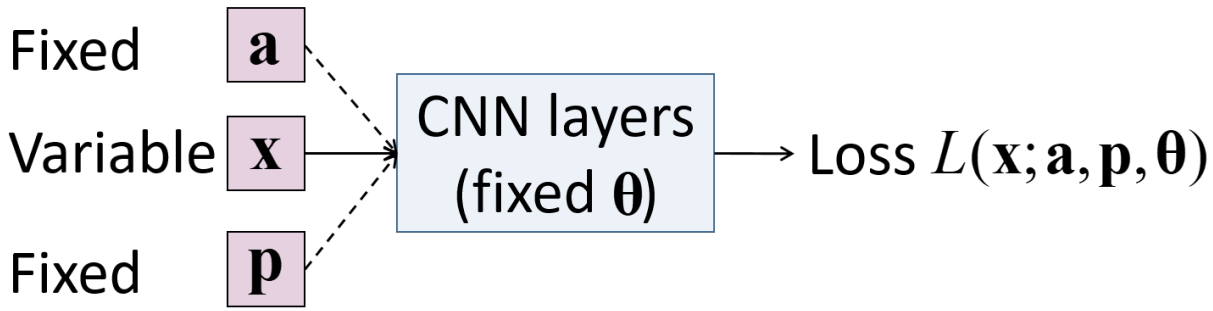
- To be optimized is not CNN parameters, but input image $\mathbf{x}$
- How is CNN model applied here?



Style transfer: loss function (cont')

- Similar content: feature maps from conv layers should be similar between $\mathbf{x}$ and $\mathbf{p}$
- Similar style: textures in feature maps should be similar between $\mathbf{x}$ and $\mathbf{a}$

Style transfer: loss function (cont')

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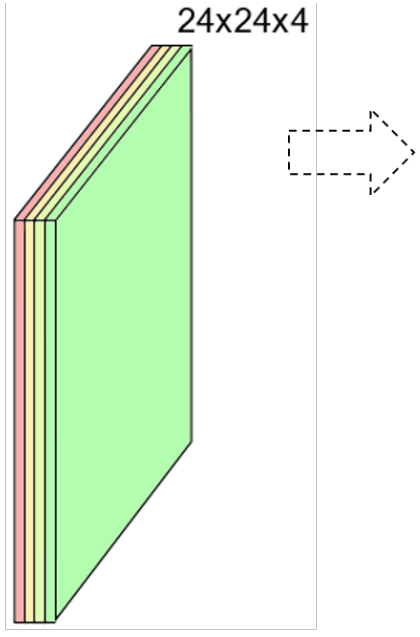
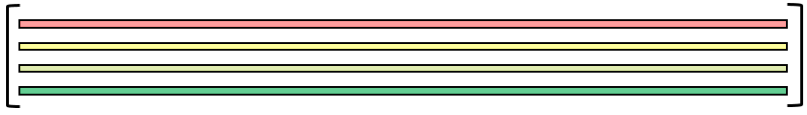


Feature maps at layer l



F^l Feature matrix of size 4×576

Gram matrix $G^l = \begin{bmatrix} G_{11} & G_{12} & G_{13} & G_{14} \\ G_{21} & G_{22} & G_{23} & G_{24} \\ G_{31} & G_{32} & G_{33} & G_{34} \\ G_{41} & G_{42} & G_{43} & G_{44} \end{bmatrix}$

$$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk}$$

Style transfer: loss function (cont')

- Content loss: measured by difference in feature matrix

$$\mathcal{L}_{content}(\mathbf{p}, \mathbf{x}) = \sum_{i,j}(F_{ij}^l - P_{ij}^l)^2$$

where F_{ij}^l is the activation of the i-th filter at position j in layer l for CNN input $\mathbf{x}$; similarly P_{ij}^l for input $\mathbf{p}$.

- Style loss: measured by difference in gram matrix

$$E_l = \sum_{i,j}(G_{ij}^l - A_{ij}^l)^2$$

$$\mathcal{L}_{style}(\mathbf{a}, \mathbf{x}) = \sum_l w_l E_l$$

where G^l and A^l are gram matrices corresponding to input $\mathbf{x}$ and $\mathbf{p}$, respectively; w_l is weighting factor.

Style transfer: loss function (cont')

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Style transfer: evaluation

- Match content on VGG layer ‘conv4_2’ and style on layers ‘conv1_1’, ‘conv2_1’, ‘conv3_1’, ‘conv4_ 1’ and ‘conv5_1’

Style transfer: evaluation

- Can easily adjust the trade-off between content and style

Figures from Gatys, Ecker, Bethge, "Image style transfer using convolutional neural networks", CVPR 2016

Style transfer: evaluation

- Lower-layer content matching kept more fine structures

Style transfer: evaluation

- Style can be transferred from one photo to another

Style Image

Content Image

Text classification

- Objective: classification of sentences or paragraph into one of predefined categories.
- E.g., sentiment analysis, news categorization

Dataset	Label	Sample
Yelp P.	+1	Been going to Dr. Goldberg for over 10 years. I think I was one of his 1st patients when he started at MHMG. Hes been great over the years and is really all about the big picture. [...]
Amz P.	3(/5)	I love this show, however, there are 14 episodes in the first season and this DVD only shows the first eight. [...]. I hope the BBC will release another DVD that contains all the episodes, but for now this one is still somewhat enjoyable.
Sogou	"Sports"	ju4 xi1n hua2 she4 5 yue4 3 ri4 , be3i ji1ng 2008 a4o yu4n hui4 huo3 ju4 jie1 li4 ji1ng guo4 shi4 jie4 wu3 da4 zho1u 21 ge4 che2ng shi4
Yah. A.	"Computer, Internet"	"What should I look for when buying a laptop? What is the best brand and what's reliable?","Weight and dimensions are important if you're planning to travel with the laptop. Get something with at least 512 mb of RAM. [..] is a good brand, and has an easy to use site where you can build a custom laptop."

Figures and tables from Conneau, Schwenk, Le Cun, Barrault, "Very deep convolutional networks for text classification", arXiv 2017

Text classification: data representation

- Every text (sentences/paragraphs) consists of (truncated or padded) 1014 characters
- A unique 16-dimensional vector to represent each character.
- So, input to CNN is a 16×1014 matrix
  Or: 16 channels, 'image' of size 1×1014 per channel

  Different from images: 1-dimensional 'image' or feature maps

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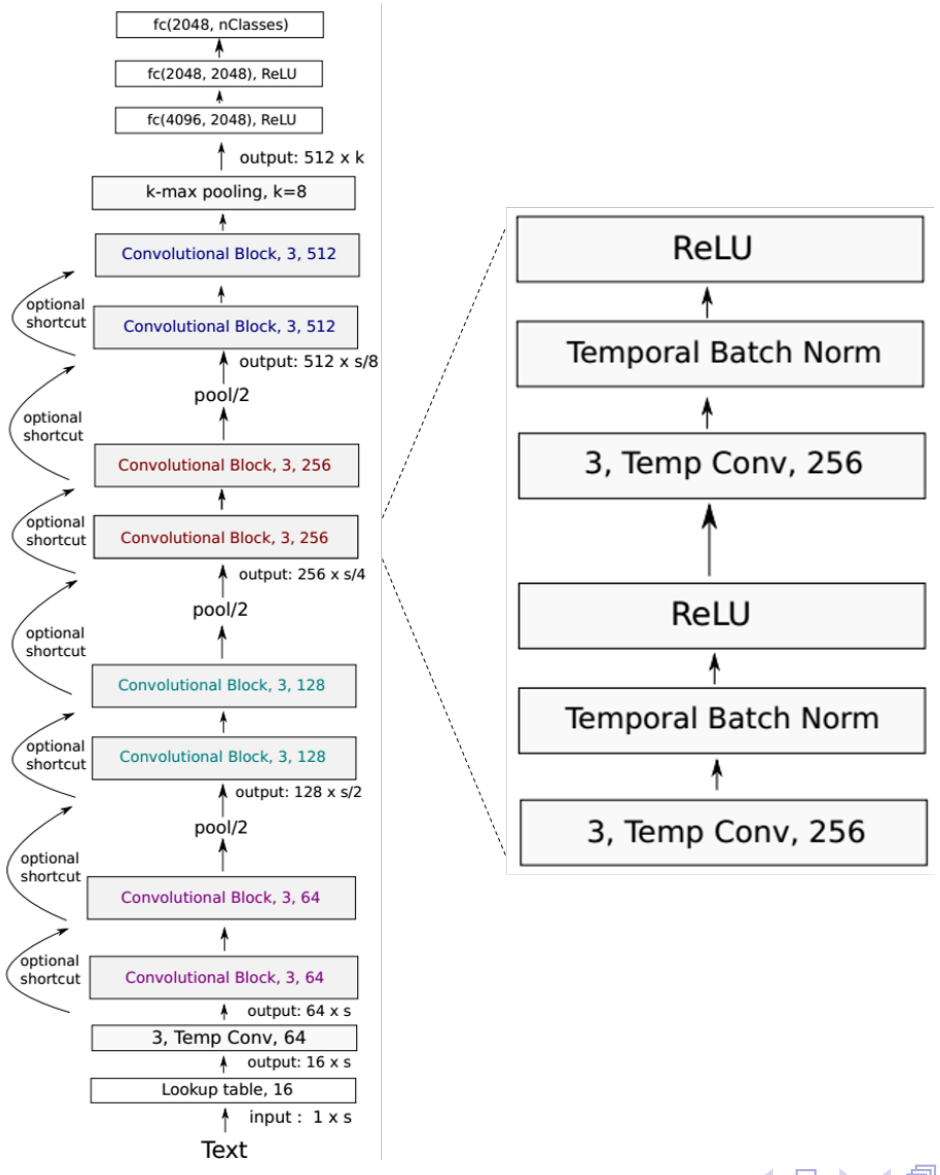
Text classification: model structure



Text classification: evaluation

Data set	#Train	#Test	#Classes	Classification Task
AG's news	120k	7.6k	4	English news categorization
Sogou news	450k	60k	5	Chinese news categorization
DBPedia	560k	70k	14	Ontology classification
Yelp Review Polarity	560k	38k	2	Sentiment analysis
Yelp Review Full	650k	50k	5	Sentiment analysis
Yahoo! Answers	1 400k	60k	10	Topic classification
Amazon Review Full	3 000k	650k	5	Sentiment analysis
Amazon Review Polarity	3 600k	400k	2	Sentiment analysis

Depth	Pooling	AG	Sogou	DBP.	Yelp P.	Yelp F.	Yah. A.	Amz. F.	Amz. P.
9	Convolution	10.17	4.22	1.64	5.01	37.63	28.10	38.52	4.94
9	KMaxPooling	9.83	3.58	1.56	5.27	38.04	28.24	39.19	5.69
9	MaxPooling	9.17	3.70	1.35	4.88	36.73	27.60	37.95	4.70
17	Convolution	9.29	3.94	1.42	4.96	36.10	27.35	37.50	4.53
17	KMaxPooling	9.39	3.51	1.61	5.05	37.41	28.25	38.81	5.43
17	MaxPooling	8.88	3.54	1.40	4.50	36.07	27.51	37.39	4.41
29	Convolution	9.36	3.61	1.36	4.35	**35.28**	27.17	37.58	**4.28**
29	KMaxPooling	**8.67**	**3.18**	1.41	4.63	37.00	27.16	38.39	4.94
29	MaxPooling	8.73	3.36	**1.29**	**4.28**	35.74	**26.57**	**37.00**	4.31

- Test error (2nd table) on 8 datasets (1st): deeper is better

Summary

- CNN extensions: denser, wider, more cardinality
- CNN applied to multiple domains
- CNN for face verification: triplet loss
- CNN for style transfer: separable via conv layers?
- CNN for text classification: each text as 1D 'image'

Further reading:

- Oord et al., Wavenet: A generative model for raw audio, arXiv, 2016
- Deng et al., ArcFace: additive angular margin loss for deep face recognition, arXiv, 2018