Нейронные сети в машинном обучении

Лекция №5
Глубинные нейронные сети

Евгений Богатырев

education

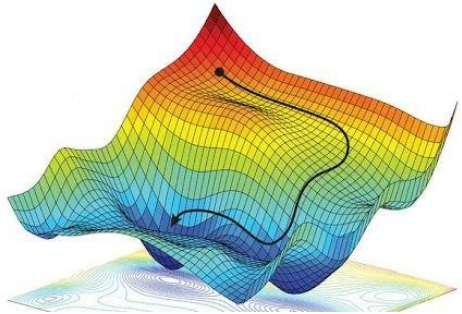
Не забывайте отмечаться
и оставлять отзывы!

Содержание

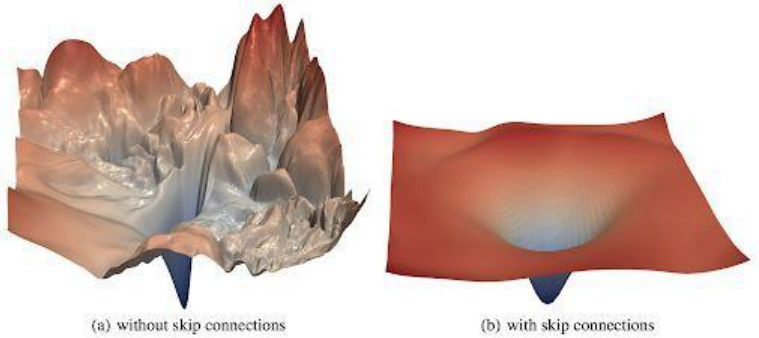
1. Оптимизации обучения
    a. Инициализация
    b. Регуляризация
    c. Нормализация
2. Архитектуры CNN
    a. LeNet
    b. AlexNet
    c. VGG
    d. ResNet
    e. Модификации ResNet
3. Сравнение моделей

Резюме с прошлого занятия

На прошлой лекции мы изучили методы оптимизации обучения нейронных сетей:



На этой лекции мы обсудим, какие еще существуют подходы, которые могут ускорить обучение и предотвратить переобучение



(a) without skip connections (b) with skip connections

Figure 1: The loss surfaces of ResNet-56 with/without skip connections. The proposed filter normalization scheme is used to enable comparisons of sharpness/flatness between the two figures.

education

Оптимизации обучения

education

Инициализация Xavier / Glorot

Рассмотрим нечетную функцию с единичной производной в нуле в качестве активации (напр. tanh)

- Хотим начать из линейного региона, чтобы избежать затухающих градиентов

$$z^{i+1} = f(\underbrace{z^i W^i}_{s^i})$$

$$\mathbb{D}[z^i] = \mathbb{D}[x] \prod_{k=0}^{i-1} n_k \mathbb{D}[W^k]$$

$$\mathbb{D}[\frac{\partial L}{\partial s^i}] = \mathbb{D}[\frac{\partial L}{\partial s^d}] \prod_{k=i}^{d} n_{k+1} \mathbb{D}[W^k]$$

Где n_i — размерность i-го слоя

Инициализация Xavier / Glorot

Хорошая инициализация:

$$\forall(i,j)\begin{cases}\mathbb{D}[z^i]=\mathbb{D}[z^j]\\ \mathbb{D}[\frac{\partial L}{\partial s^i}]=\mathbb{D}[\frac{\partial L}{\partial s^j}]\end{cases}$$

Это эквивалентно следующему:

$$\forall i\begin{cases}n_i\mathbb{D}[W^i]=1\\ n_{i+1}\mathbb{D}[W^i]=1\end{cases}$$

Компромисс:

$$\mathbb{D}[W^i]=\frac{2}{n_i+n_{i+1}}$$

$$W^i\sim U[-\frac{\sqrt{6}}{\sqrt{n_i+n_{i+1}}},\frac{\sqrt{6}}{\sqrt{n_i+n_{i+1}}}]$$

Инициализация He

Рассмотрим ReLU в качестве активации:

- Функция не симметрична
- Не дифференцируема в нуле

$$\mathbb{D}[z^i] = \mathbb{D}[x](\prod_{k=0}^{i-1} \frac{1}{2} n_k \mathbb{D}[W^k]) \Rightarrow \mathbb{D}[W^k] = \frac{2}{n_k}$$

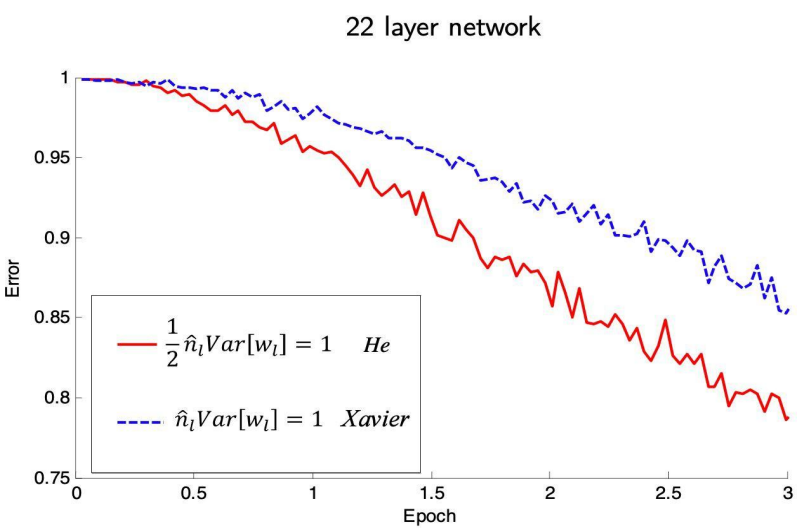
$$\mathbb{D}[\frac{\partial L}{\partial s^i}] = \mathbb{D}[\frac{\partial L}{\partial s^d}](\prod_{k=i}^{d} \frac{1}{2} n_{k+1} \mathbb{D}[W^k]) \Rightarrow \mathbb{D}[W^k] = \frac{2}{n_{k+1}}$$

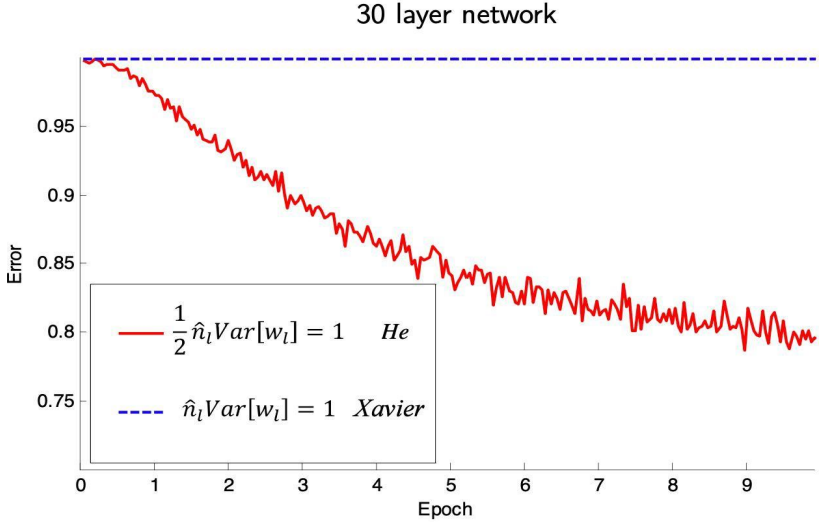
$$\mathbb{D}[\frac{\partial L}{\partial s^i}] = \mathbb{D}[\frac{\partial L}{\partial s^d}] \prod_{k=1}^{d} \frac{1}{2} n_{k+1} \mathbb{D}[W^k] = \frac{n_2}{n_d} \mathbb{D}[\frac{\partial L}{\partial s^d}]$$

$$W^i \sim N(0, \frac{2}{n_i})$$
or
$$W^i \sim N(0, \frac{2}{n_{i+1}})$$

Kaiming He et al.: Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification, 2015 https://arxiv.org/pdf/1502.01852

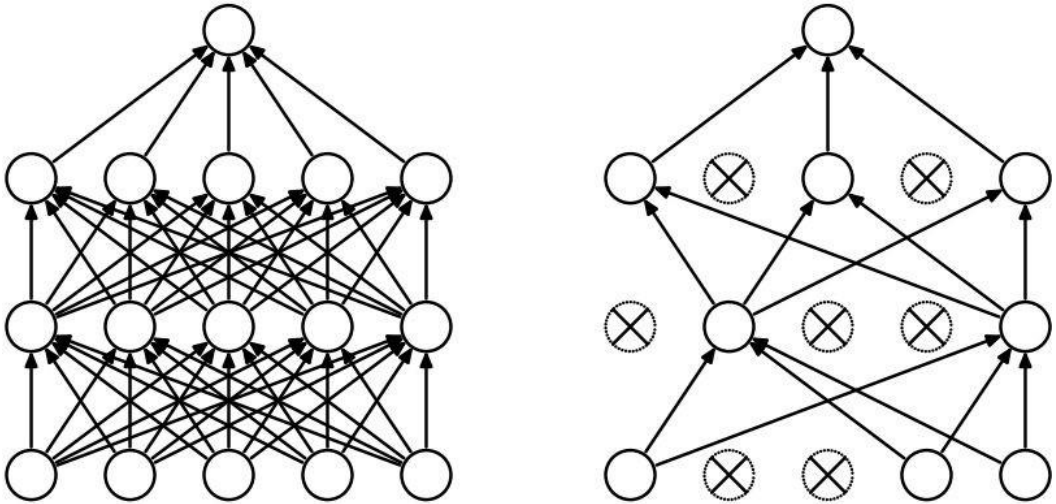
Инициализация He





Kaiming He et al.: Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification, 2015 https://arxiv.org/pdf/1502.01852

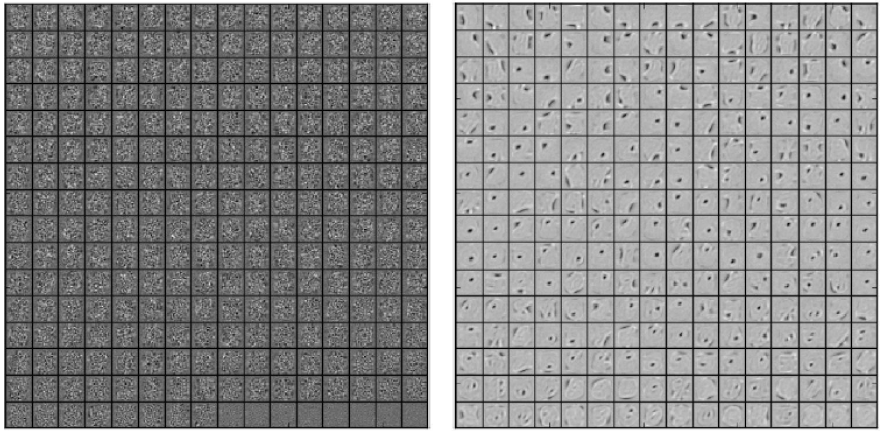
Регуляризация: Dropout



- С вероятностью p занулим выход нейрона (например, p = 0.5)
- В test-time домножаем веса на вероятность сохранения
- Не стоит выкидывать нейроны последнего слоя

Регуляризация: Dropout

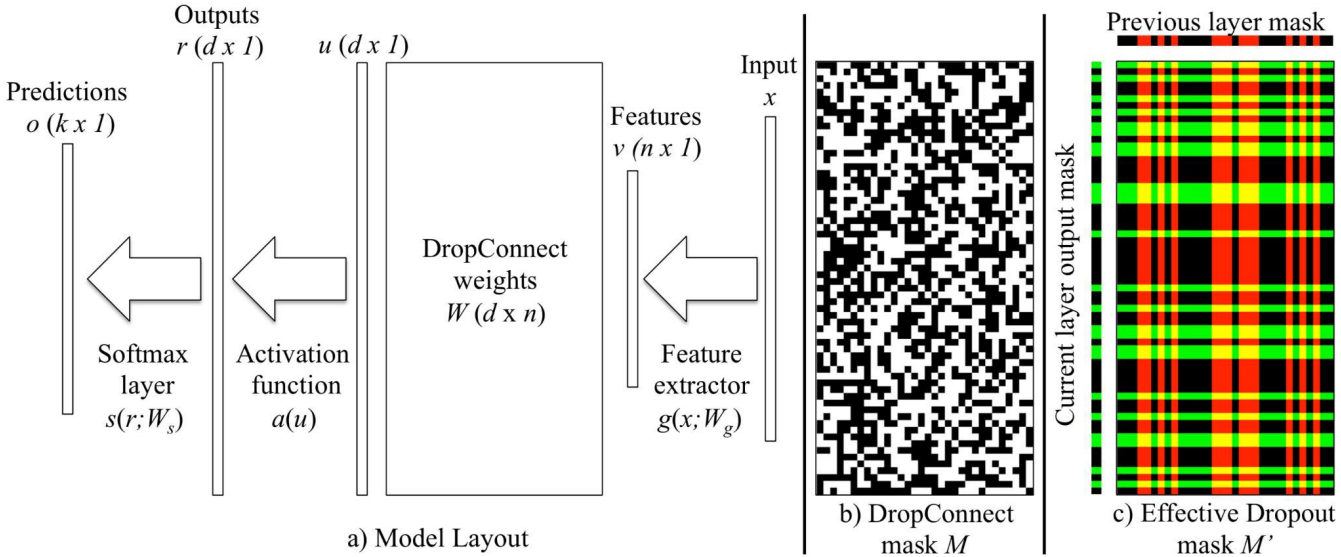
- Борьба с коадаптацией – нейроны больше не могут рассчитывать на наличие соседей
- Биология: не все гены родителей будут присутствовать у потомков
- Усреднение большого (2n) числа моделей



Выученные признаки на MNIST.
Слева: без Dropout, справа – с Dropout

Регуляризация: Dropconnect

Зануляем не выходы нейронов, а каждый вес по отдельности



education

Batch Norm

- Covariate shift: изменение распределения входов во время обучения
- Цель — уменьшить covariate shift скрытых слоев
- Нормализуем значения по батчу
- Для инференса накапливаем статистику экспоненциальным средним

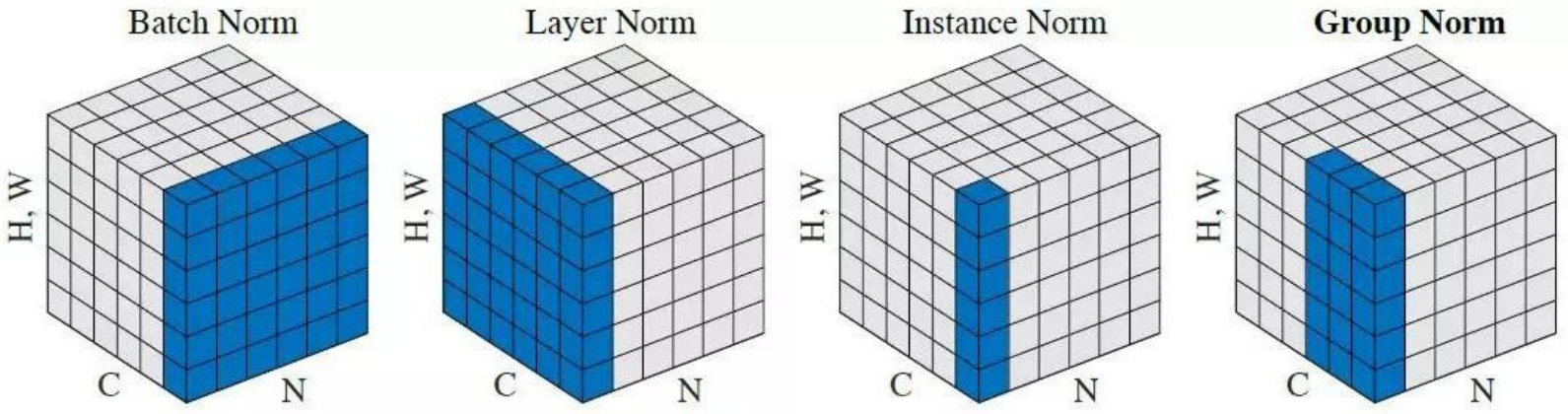
$$E_{i+1} = (1-\alpha)E_i + \alpha E_{\mathcal{B}}$$

$$\hat{x} = \frac{x - \mathbb{E}[x]}{\sqrt{\mathbb{D}[x] + \epsilon}}$$

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

$$y = \frac{\gamma}{\sqrt{\mathbb{D}[x] + \epsilon}} \cdot x + (\beta - \frac{\gamma \mathbb{E}[x]}{\sqrt{\mathbb{D}[x] + \epsilon}})$$

Нормализация



	Weight matrix re-scaling	Weight matrix re-centering	Weight vector re-scaling	Dataset re-scaling	Dataset re-centering	Single training case re-scaling
Batch norm	Invariant	No	Invariant	Invariant	Invariant	No
Weight norm	Invariant	No	Invariant	No	No	No
Layer norm	Invariant	Invariant	No	Invariant	No	Invariant

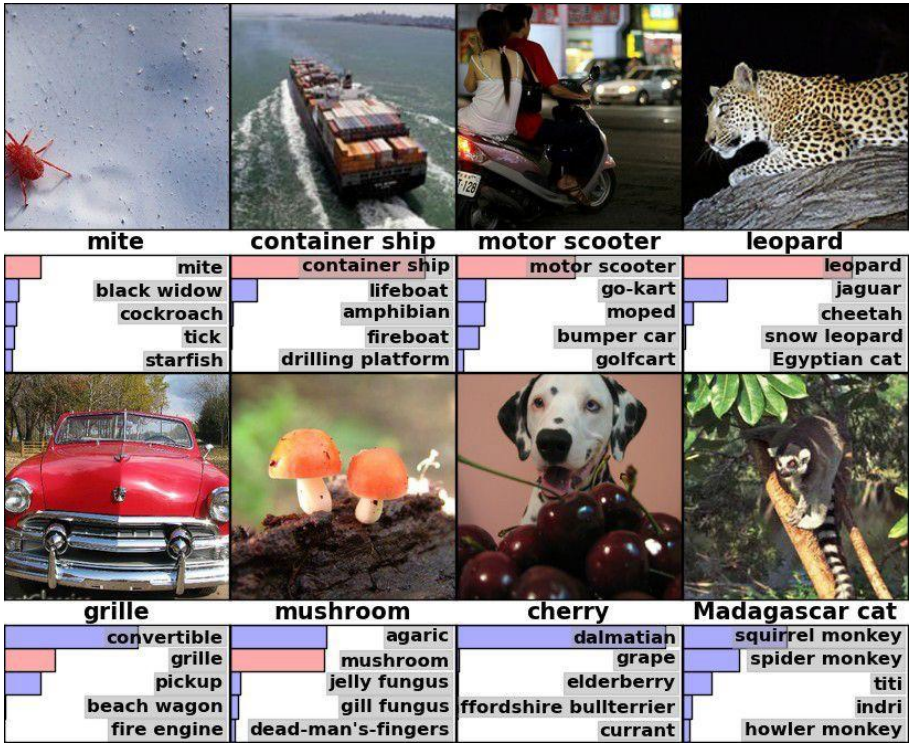
Архитектуры CNN

education

Датасет ImageNet

IMAGENET

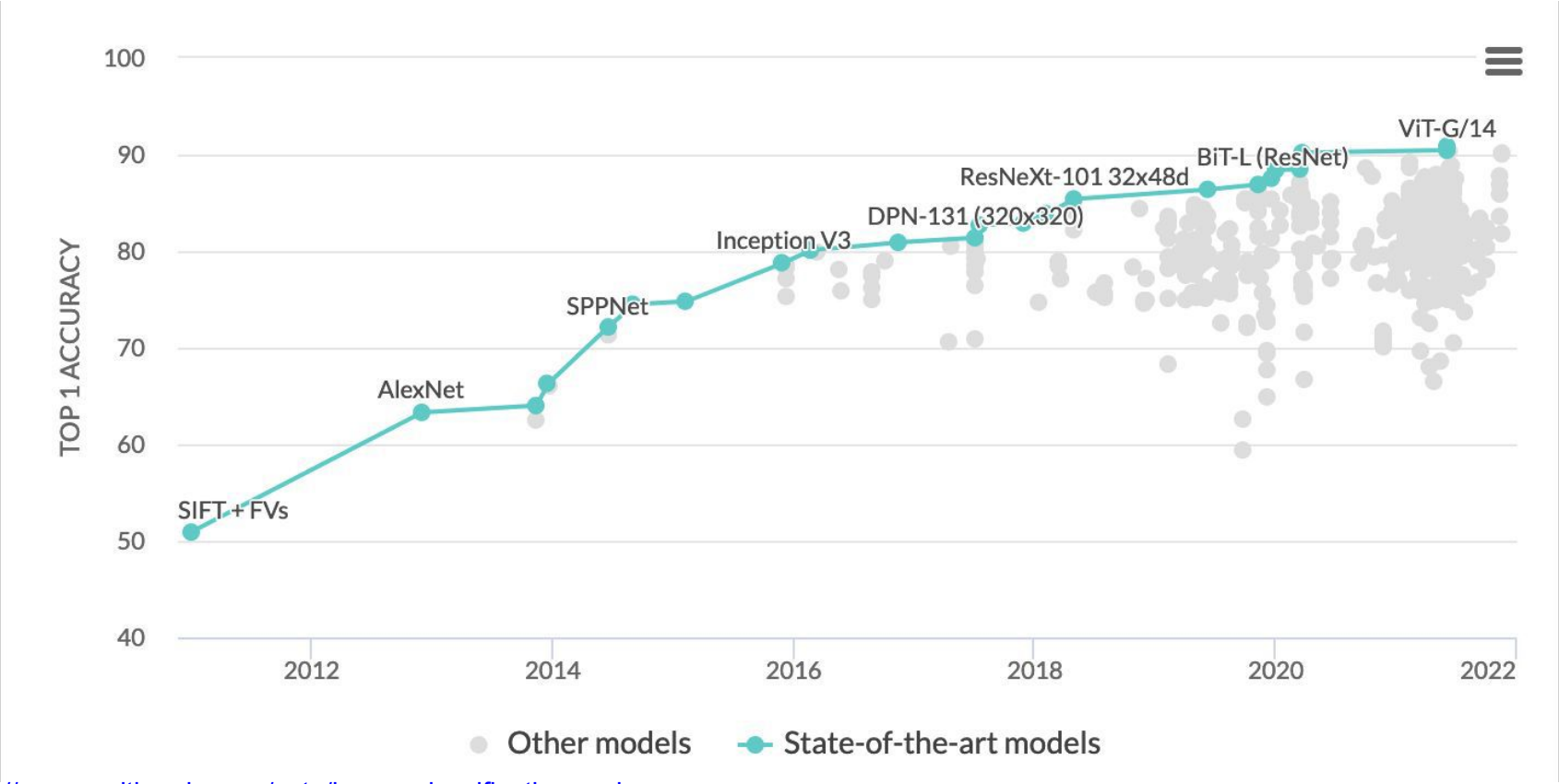
- 1000 классов
- Около 1000 изображений в каждом классе
- Около 1 000 000 изображений всего
- Несколько номинаций: таких как распознавание и детектирование/локализация



Примеры предсказаний на ImageNet

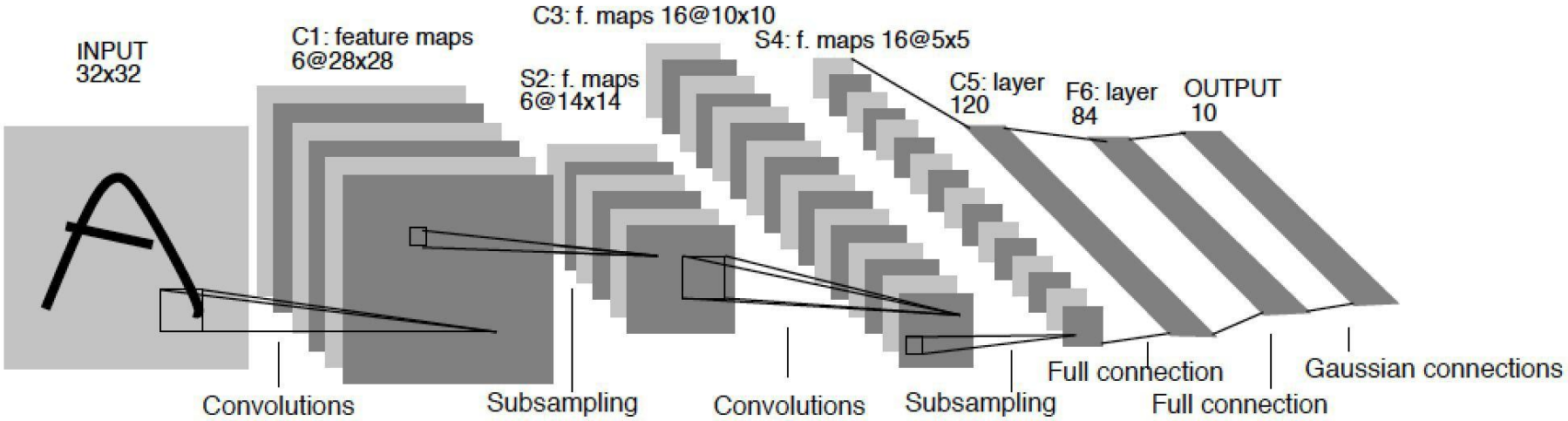
education

Прогресс на ImageNet



https://paperswithcode.com/sota/image-classification-on-image

LeNet (1989)

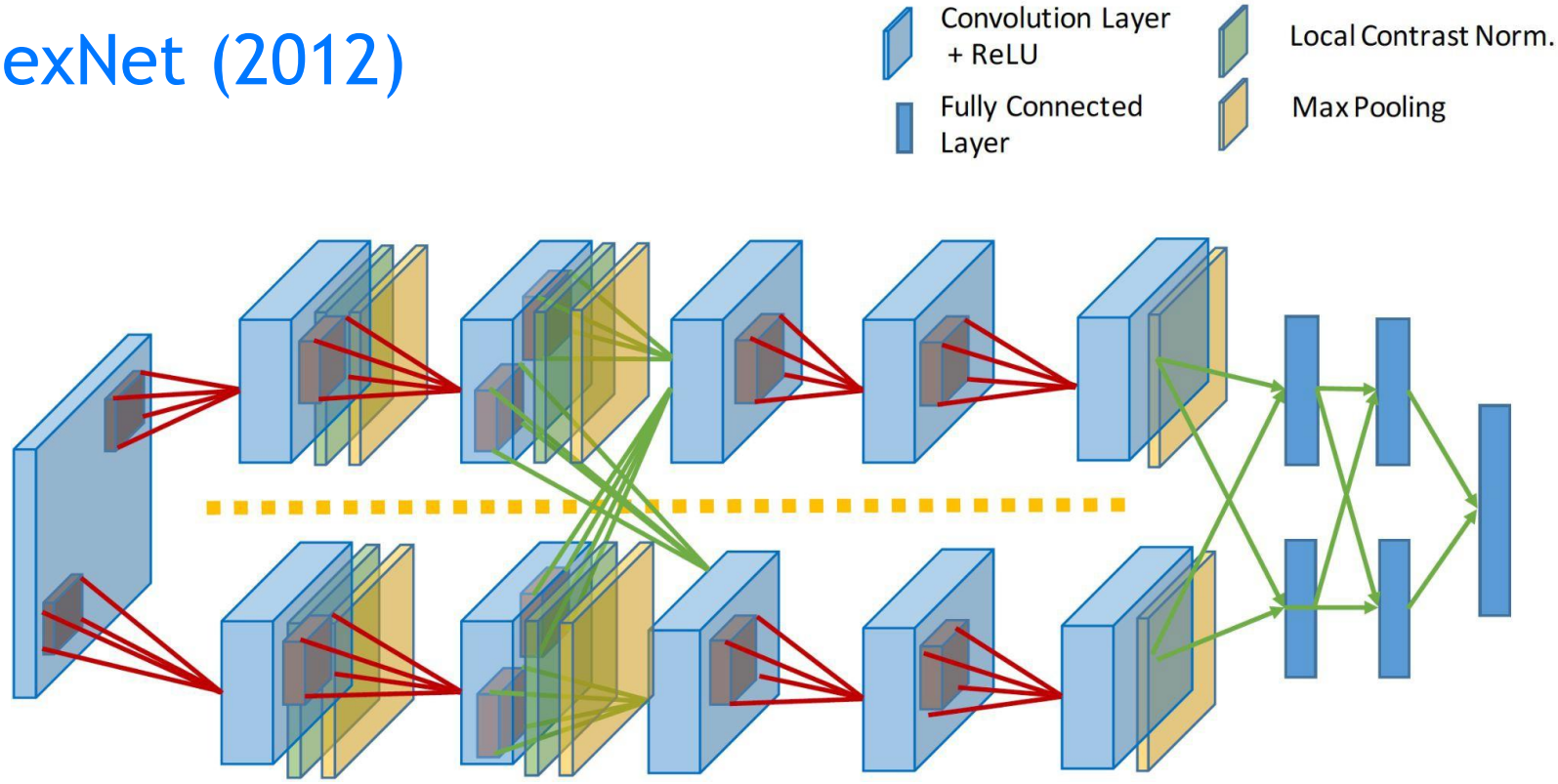


Использованные подходы:

- Сверточные слои
- Активация sigmoid
- Max pooling

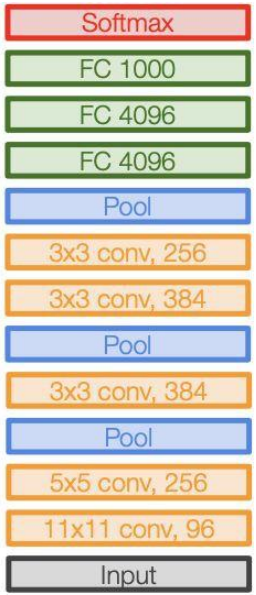
http://yann.lecun.com/exdb/lenet

AlexNet (2012)



Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton: ImageNet Classification with Deep Convolutional Neural Networks, 2012 http://www.cs.toronto.edu/~fritz/absps/imagenet.pdf

AlexNet (2012)



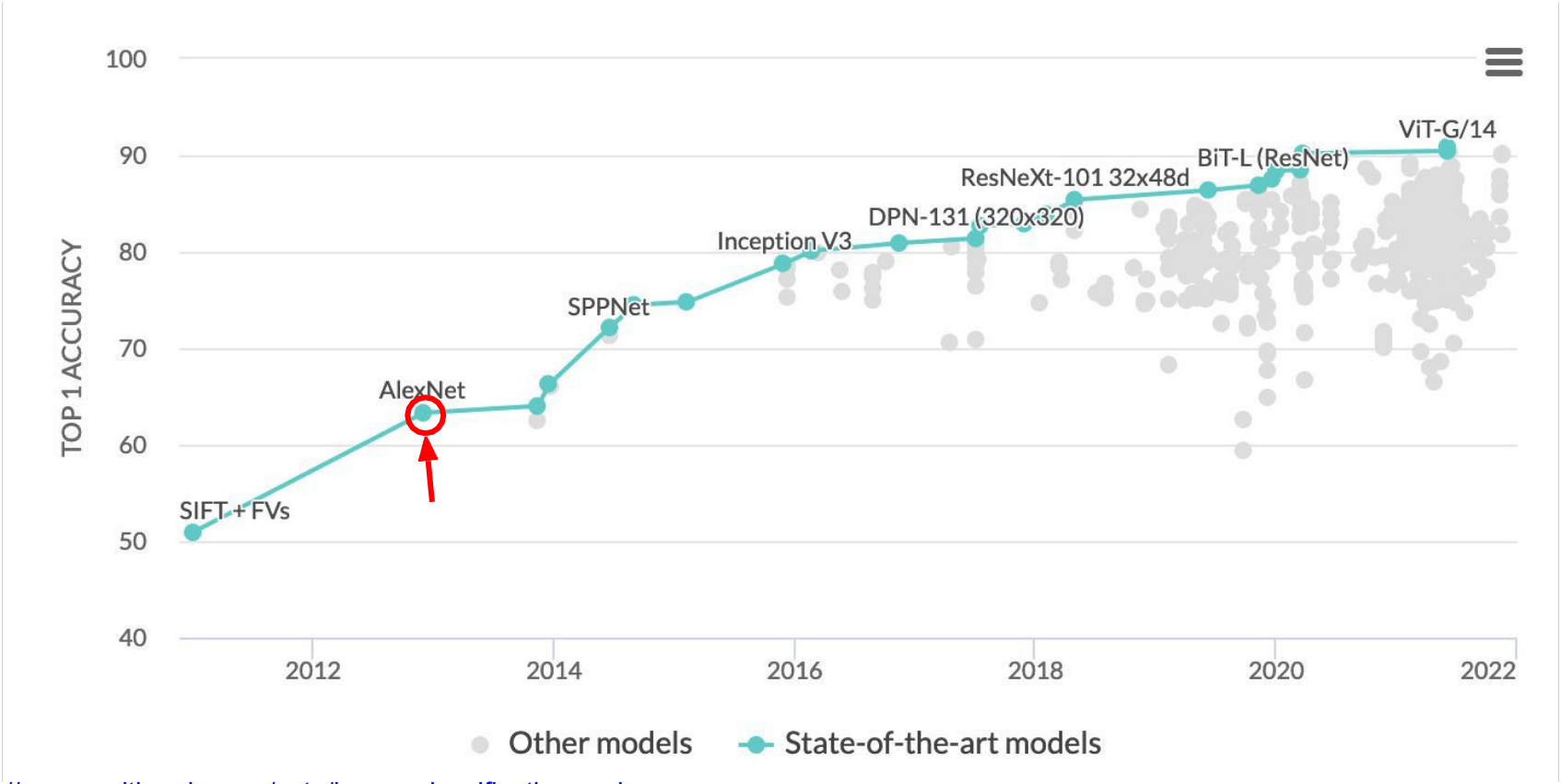
AlexNet

Source: Stanford CS231n lecture 6

- 5 сверточных и 3 полносвязных слоя
- 60M параметров
- Распараллеливание на 2 GPU
- Свёртки 11x11, 5x5, 3x3
- ReLU, т.к. не надо вычислять exp
- Dropout
- Затухание learning rate
- Аугментации: случайный 224x224 кроп, горизонтальное отражение, шум

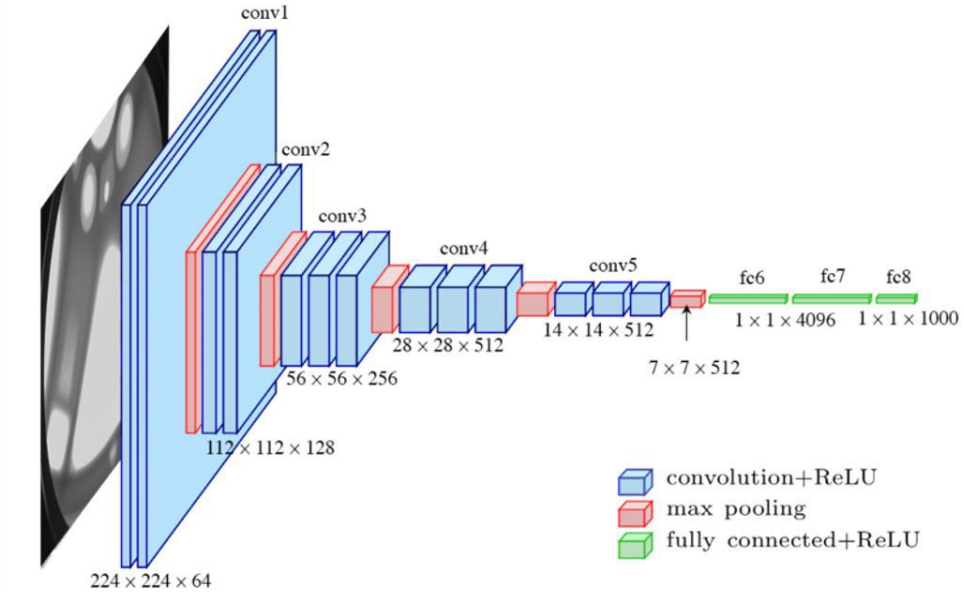
Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton: ImageNet Classification with Deep Convolutional Neural Networks, 2012 http://www.cs.toronto.edu/~fritz/absps/imagenet.pdf

Прогресс на ImageNet: AlexNet



https://paperswithcode.com/sota/image-classification-on-image

VGG (2014)

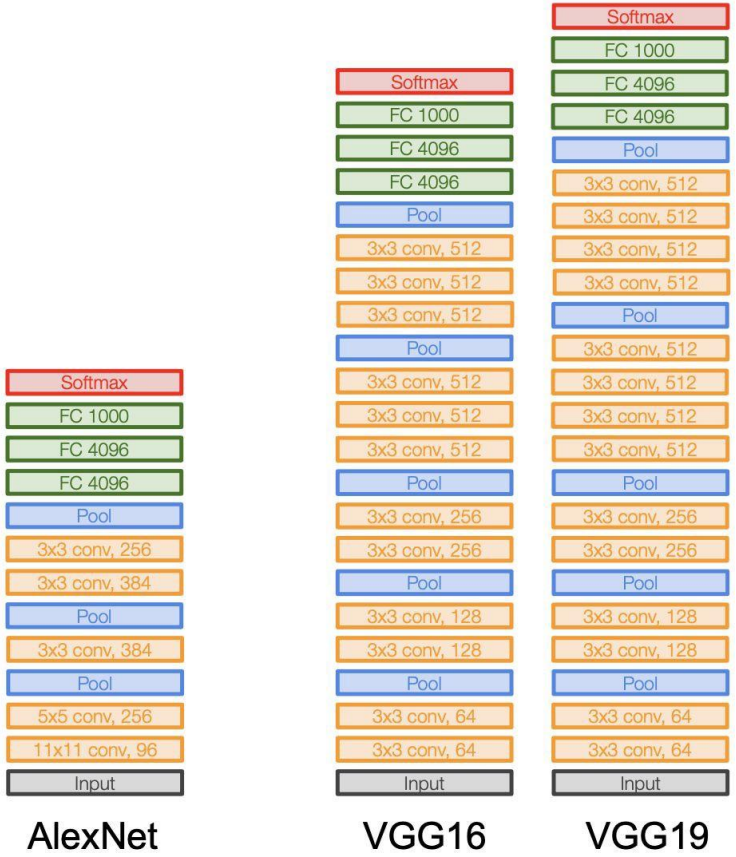


VGG-16 architecture

Karen Simonyan, Andrew Zisserman: Very Deep Convolutional Networks for Large-Scale Image Recognition, 2014 https://arxiv.org/pdf/1409.1556.pdf

VGG (2014)

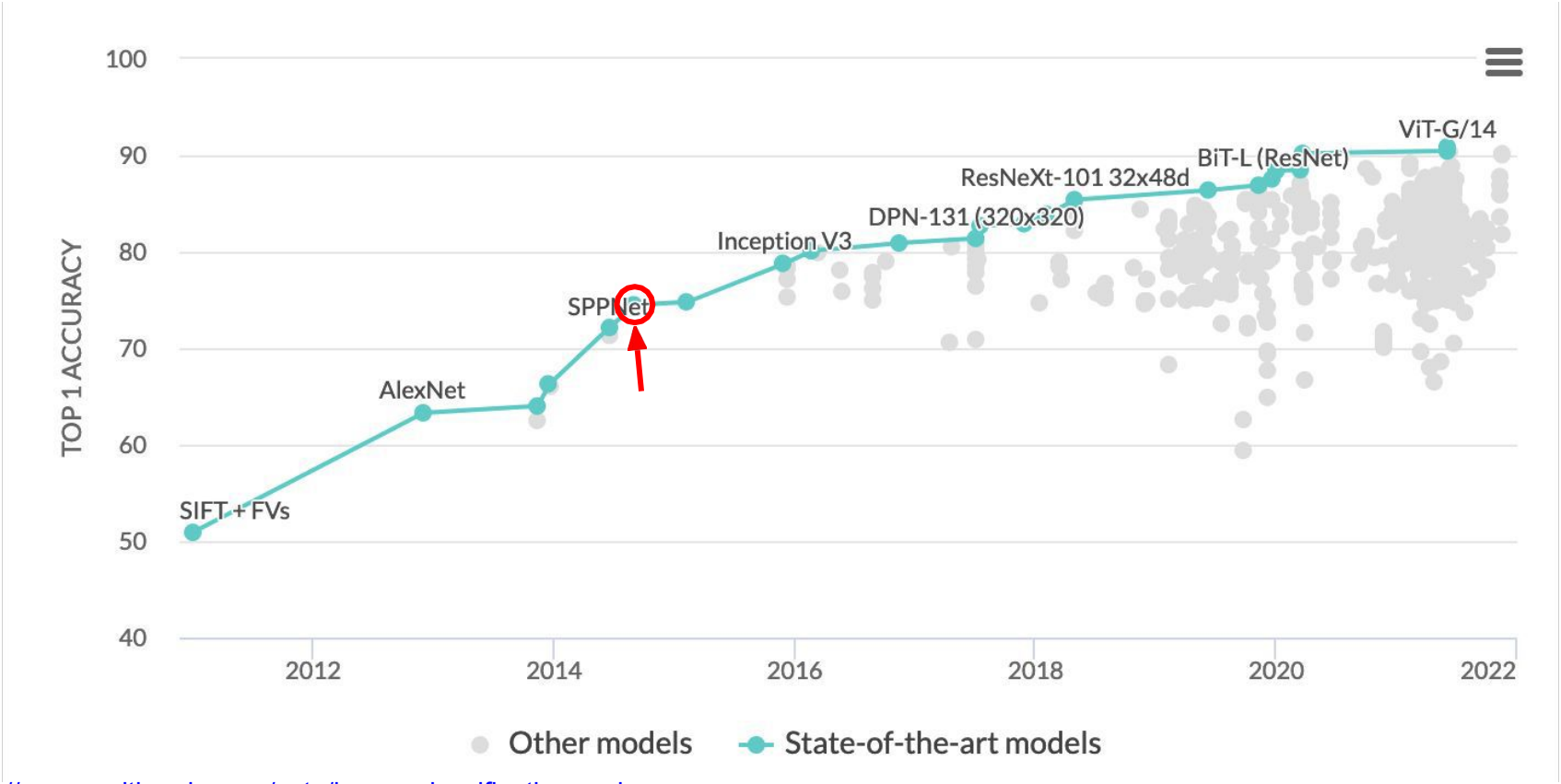
- VGG-19 (E): 144M параметров
- Только свертки 3x3
- Больше слоев (Deep Neural Network)
- Выходы промежуточных слоев можно использовать как “семантику” изображения:
  - в качестве функции потерь https://arxiv.org/abs/1603.08155
  - для переноса стиля https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Gatys_Image_Style_Transfer_CVPR_2016_paper.pdf
  - для оценки качества https://arxiv.org/abs/1801.03924



Source: Stanford CS231n lecture 6

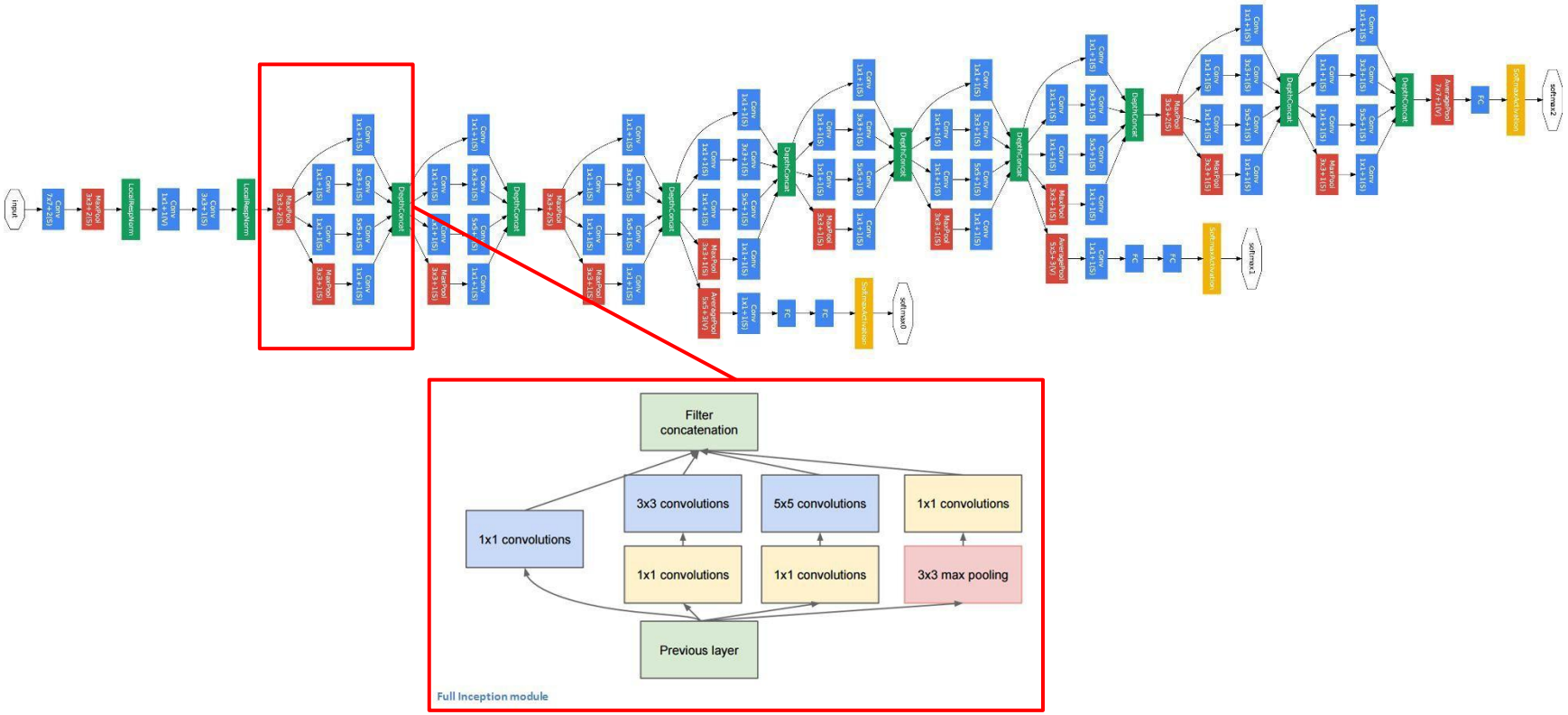
Karen Simonyan, Andrew Zisserman: Very Deep Convolutional Networks for Large-Scale Image Recognition, 2014 https://arxiv.org/pdf/1409.1556.pdf

Прогресс на ImageNet: VGG



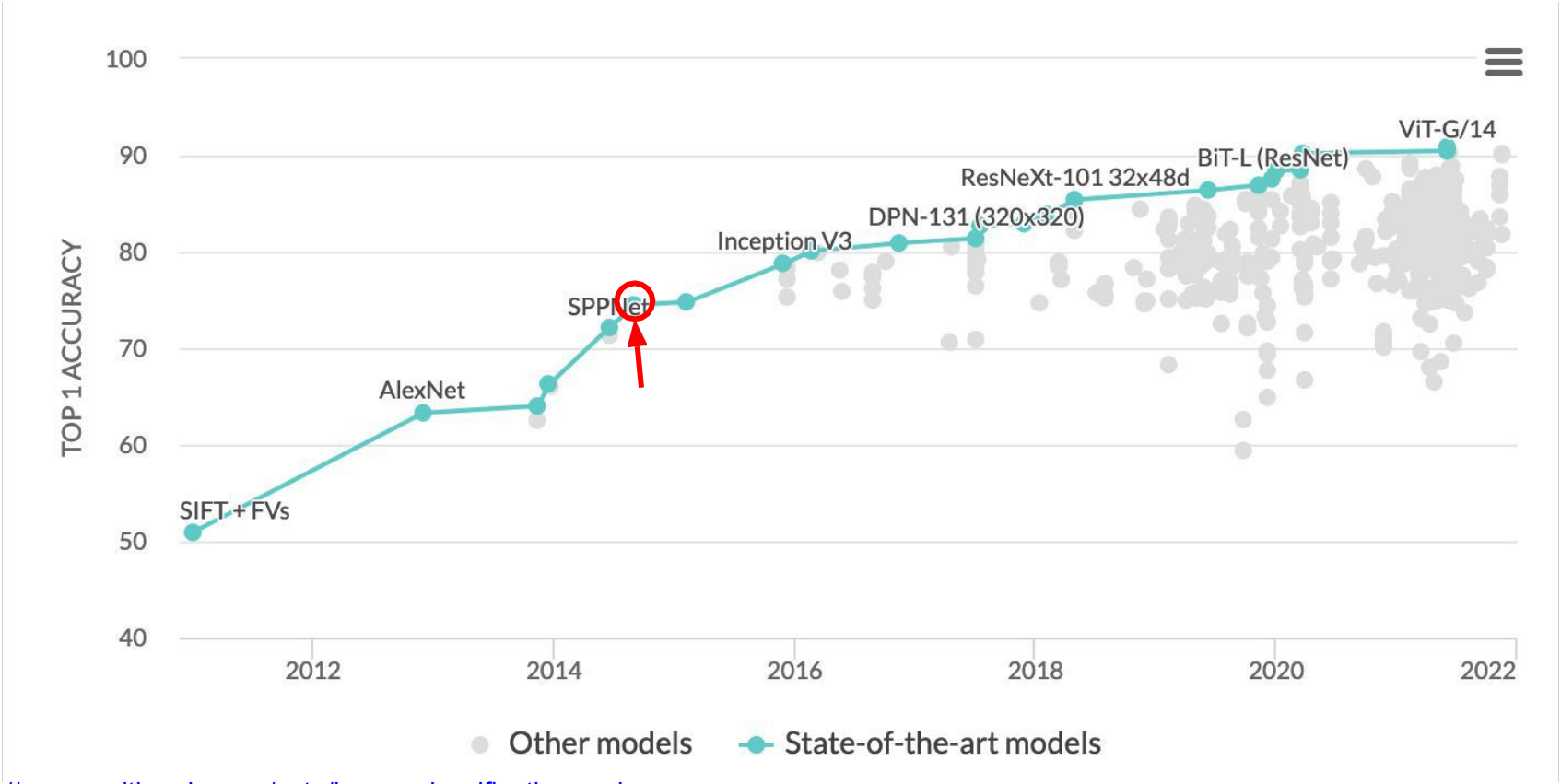
https://paperswithcode.com/sota/image-classification-on-image

GoogLeNet / Inception (2014)



Christian Szegedy et al.: Going Deeper with Convolution, 2014 https://arxiv.org/pdf/1409.4842

Прогресс на ImageNet: GoogLeNet

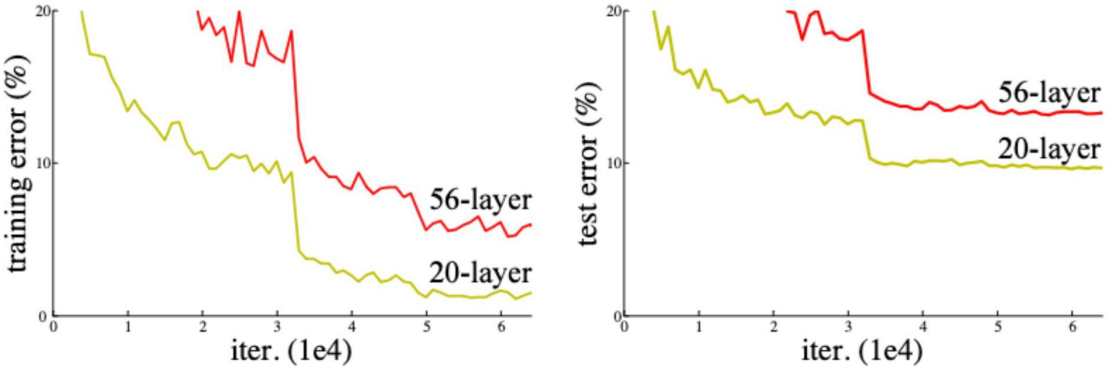


https://paperswithcode.com/sota/image-classification-on-image

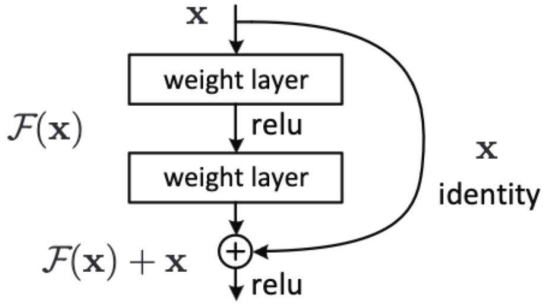
Скачок глубины нейронных сетей

http://josephpcohen.com/w/visualizing-cnn-architectures-side-by-side-with-mxnet/

ResNet (2015)



Обучение “обычной сети”

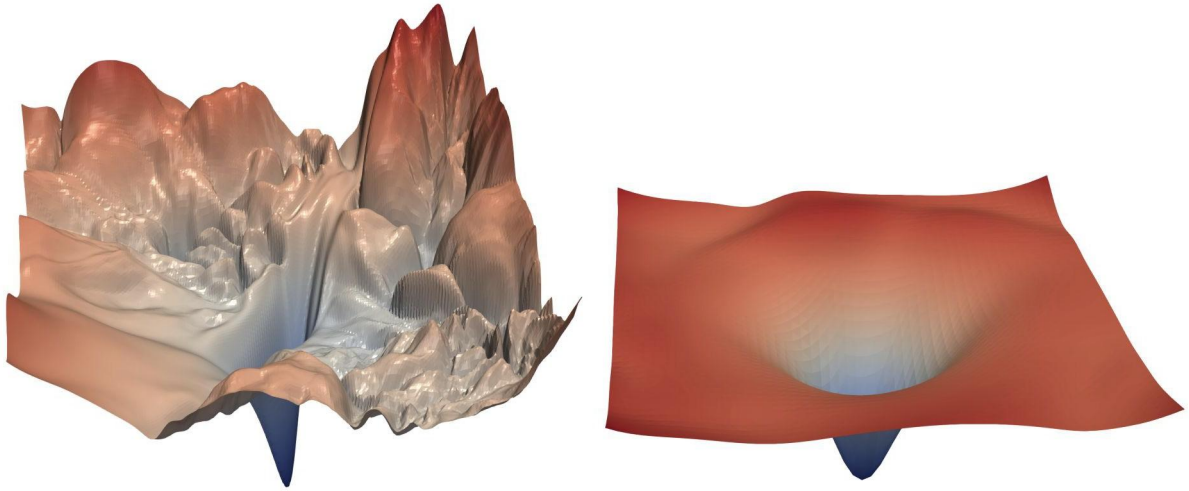


Residual block

- Результат на 56 слоях хуже. Проблема не в переобучении
- Решение заведомо существует: 20 слоев, затем F(x) = x
- Выучить F(x) = x тяжело, а F(x) = 0 просто
- Residual block решает эту проблему

Kaiming He et al.: Deep Residual Learning for Image Recognition, 2015 https://arxiv.org/pdf/1512.03385v1.pdf

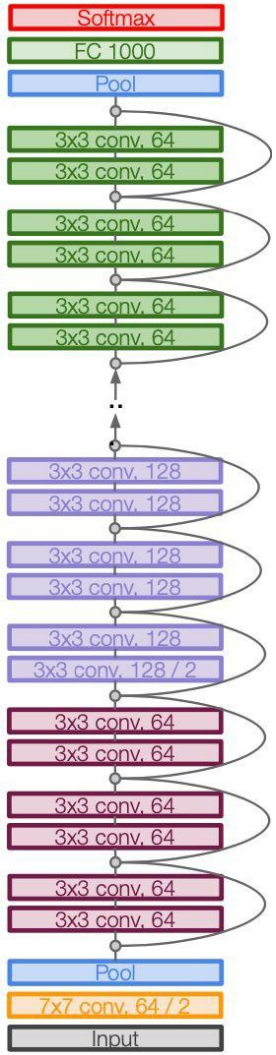
ResNet (2015)



(a) without skip connections (b) with skip connections

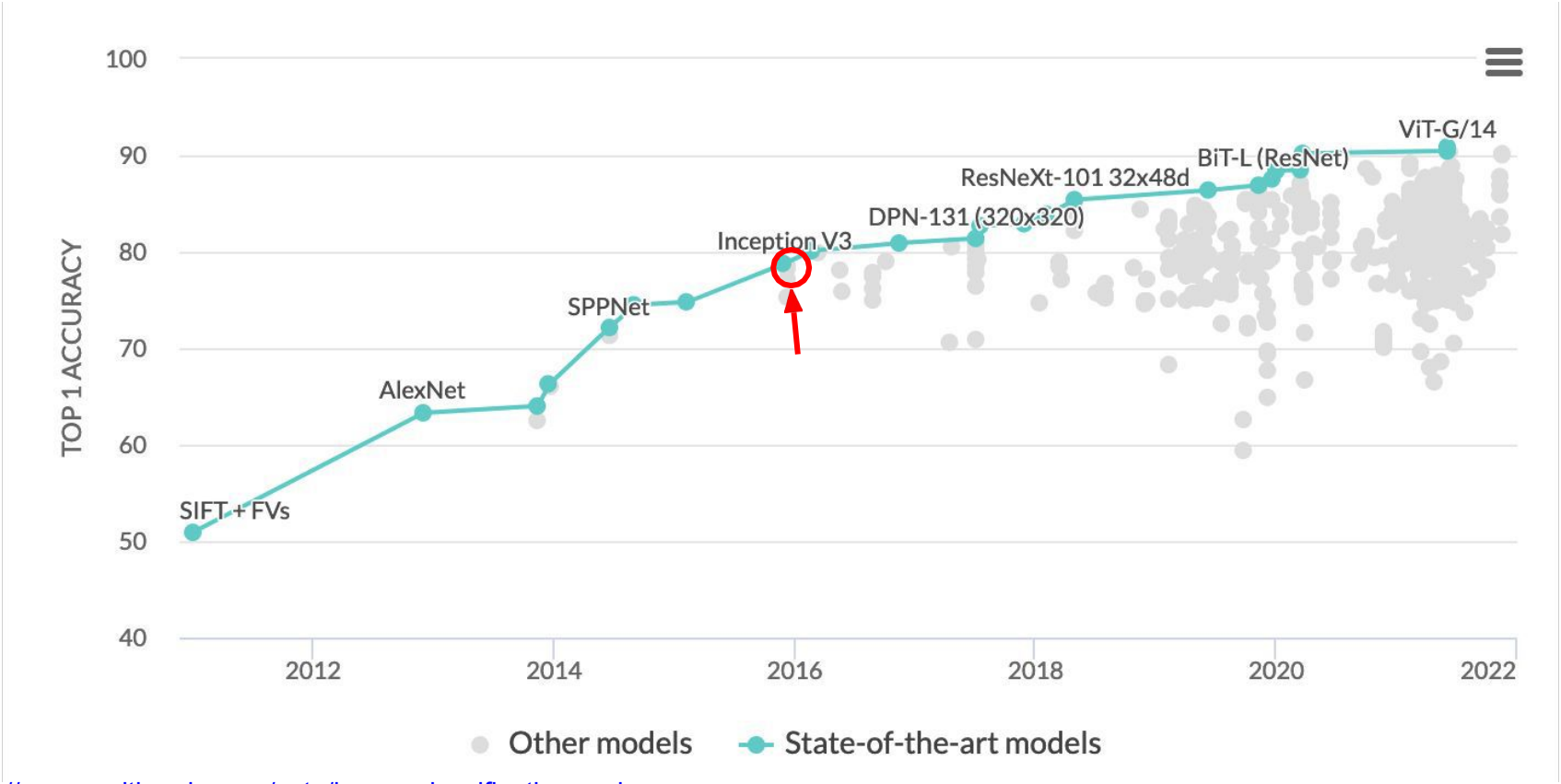
Figure 1: The loss surfaces of ResNet-56 with/without skip connections. The proposed filter normalization scheme is used to enable comparisons of sharpness/flatness between the two figures.

32nd Conference on Neural Information Processing Systems (NIPS 2018), Montréal, Canada.



Kaiming He et al.: Deep Residual Learning for Image Recognition, 2015 https://arxiv.org/pdf/1512.03385v1.pdf
https://arxiv.org/pdf/1712.09913.pdf

Прогресс на ImageNet: ResNet



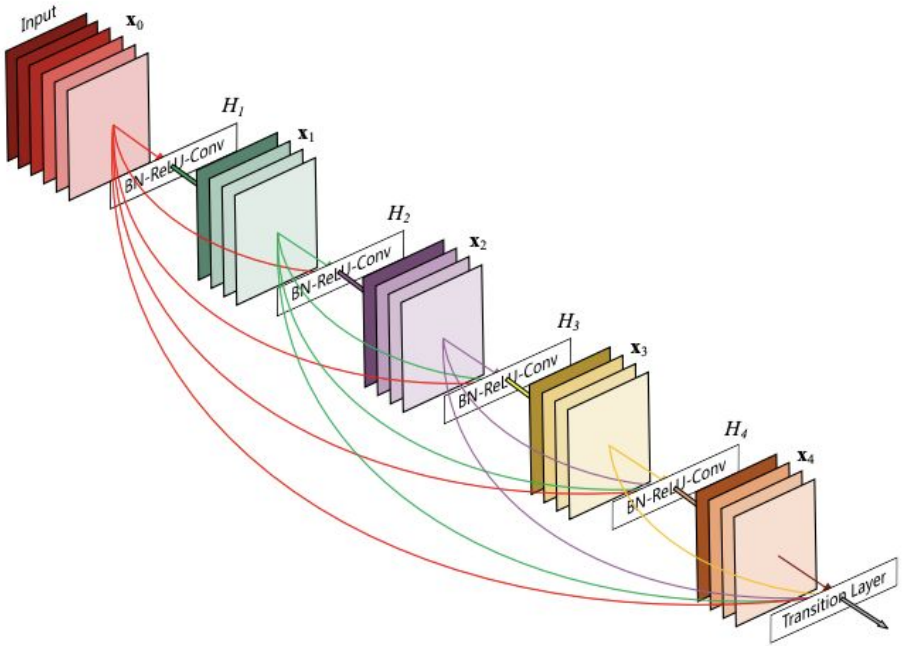
https://paperswithcode.com/sota/image-classification-on-image

Модификации моделей

Существует множество модификаций ResNet:

- ResNet in ResNet
- DenseNet
- ResNeXt
- WideResNets

DenseNet



education

ResNeXt

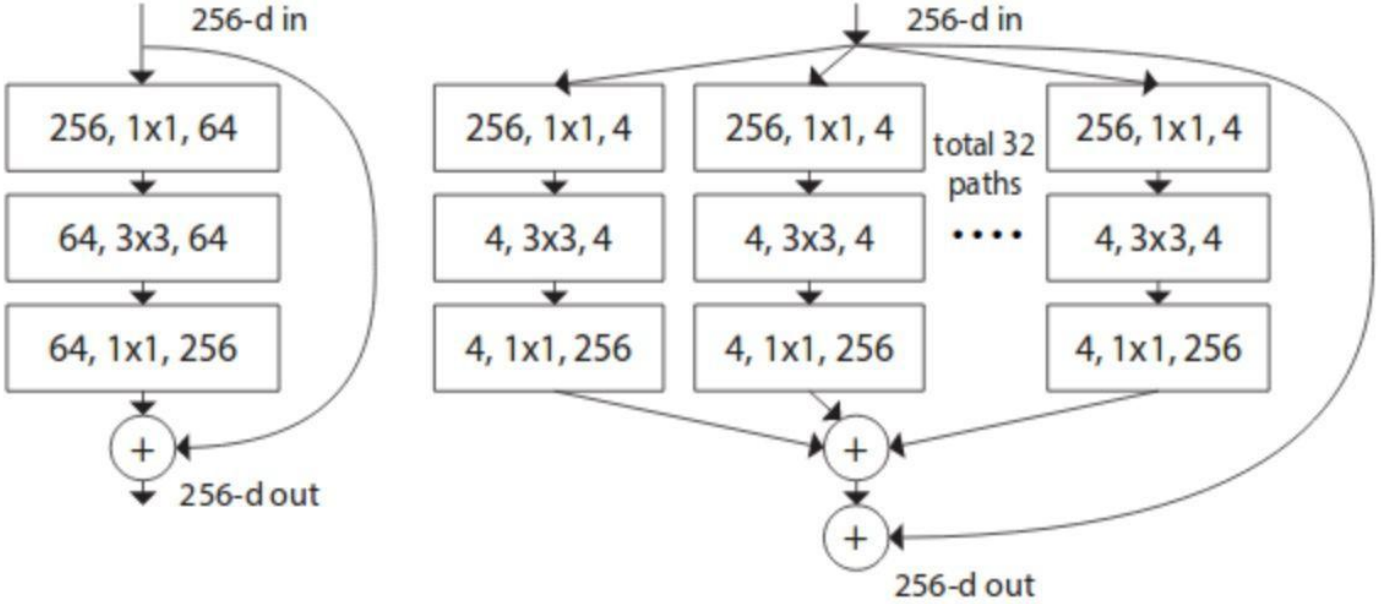


Figure 1. **Left**: A block of ResNet [14]. **Right**: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).

education

ResNet (left) and ResNeXt (right) Architecture.

Сравнение моделей

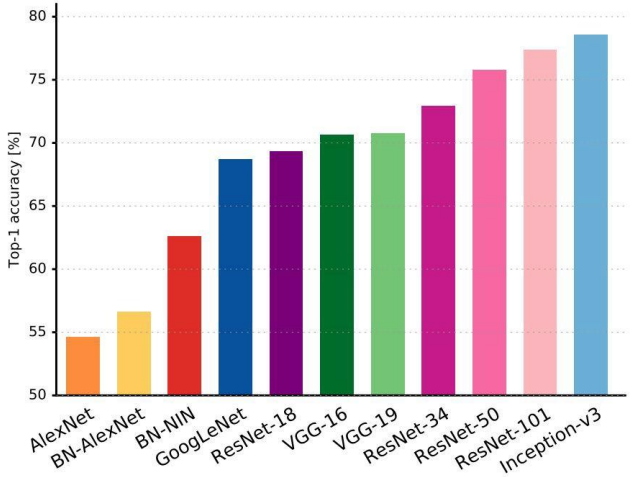


Figure 1: **Top1 *vs.* network.** Single-crop top-1 validation accuracies for top scoring single-model architectures. We introduce with this chart our choice of colour scheme, which will be used throughout this publication to distinguish effectively different architectures and their correspondent authors. Notice that network of the same group share colour, for example ResNet are all variations of pink.

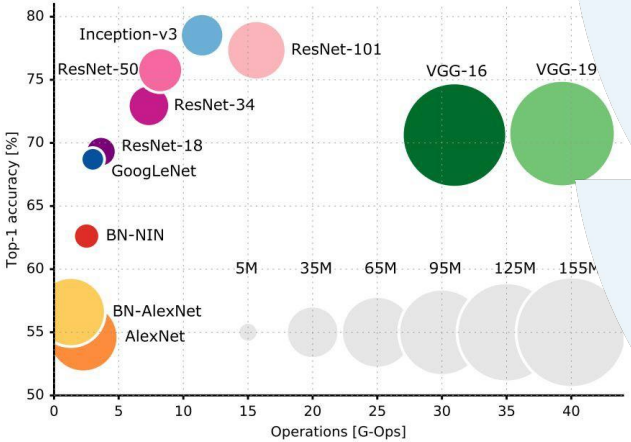
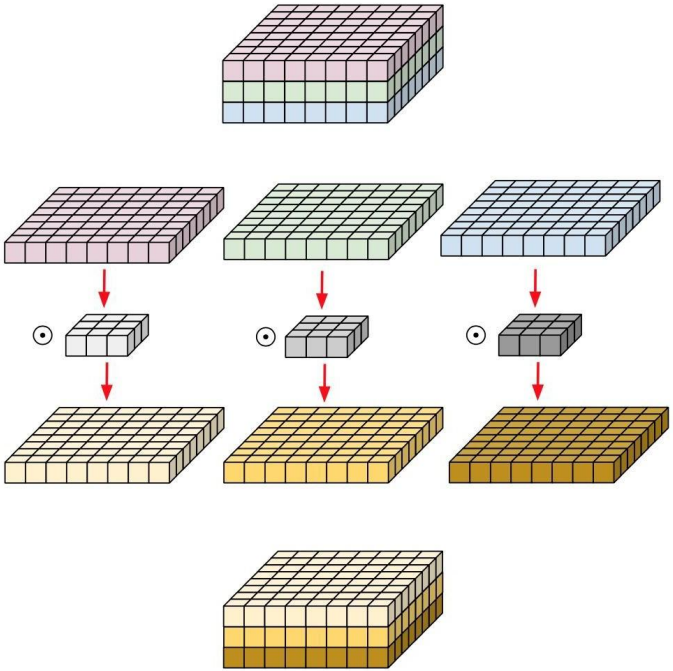


Figure 2: **Top1 *vs.* operations, size $\propto$ parameters.** Top-1 one-crop accuracy versus amount of operations required for a single forward pass. The size of the blobs is proportional to the number of network parameters; a legend is reported in the bottom right corner, spanning from 5×10^6 to 155×10^6 params.

MobileNet



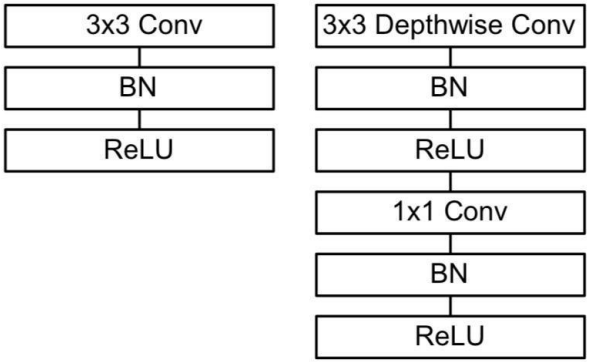
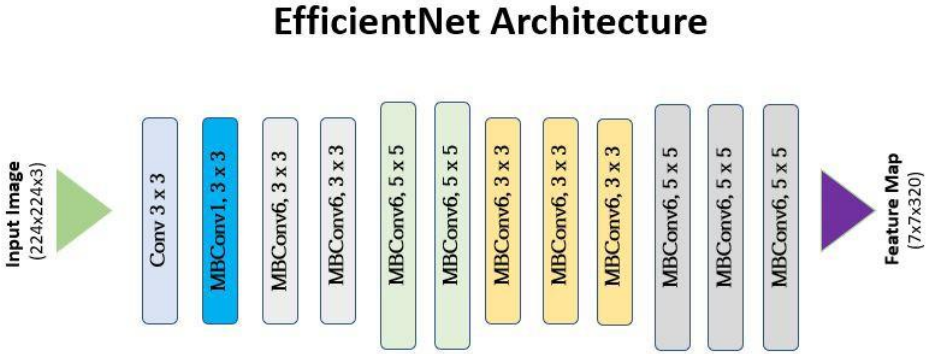


Figure 3. Left: Standard convolutional layer with batchnorm and ReLU. Right: Depthwise Separable convolutions with Depthwise and Pointwise layers followed by batchnorm and ReLU.

EfficientNet



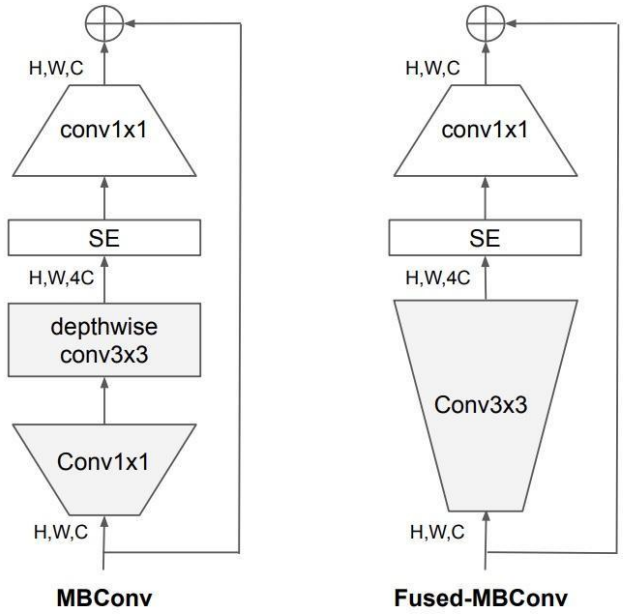
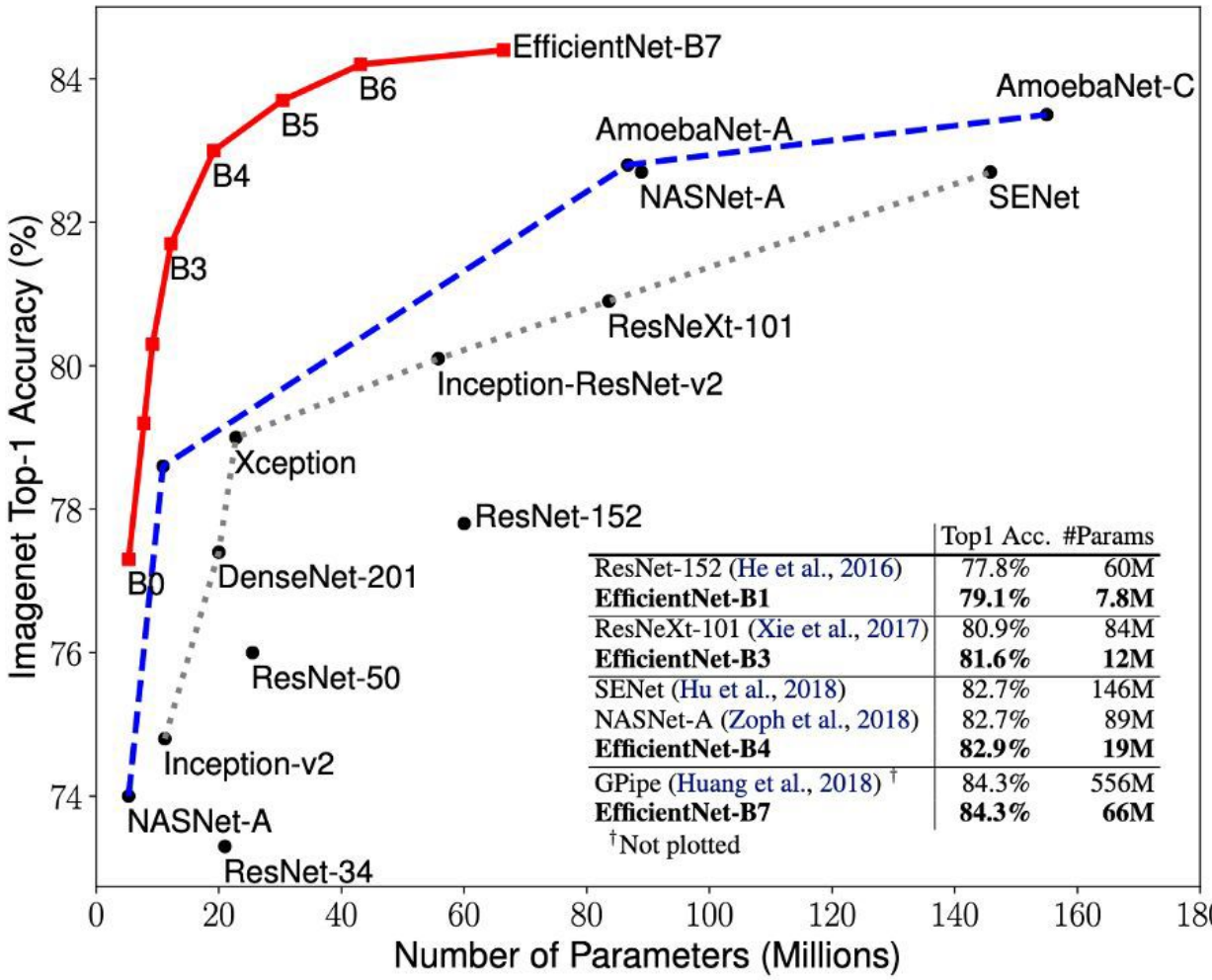


Figure 2. Structure of MBConv and Fused-MBConv.

education

EfficientNet



	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**79.1%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.6%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.9%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.3%**	**66M**

†Not plotted

education

Резюме

В этой лекции мы изучили:

1. Подходы к оптимизации обучения:
   a. Инициализация
   b. Регуляризация
   c. Нормализация

2. Архитектуры CNN и качество их работы на бенчмарке ImageNet

Рекомендованные источники

1. Kaiming He et al, “Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification,” 2015 Available online
2. ImageNet benchmark – https://paperswithcode.com/sota/image-classification-on-imagenet
3. Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks”, 2012 Available online
4. Karen Simonyan, Andrew Zisserman, “Very Deep Convolutional Networks for Large-Scale Image Recognition,” 2014 Available online
5. Christian Szegedy et al, “Going Deeper with Convolution”, 2014 Available online
6. Kaiming He et al, “Deep Residual Learning for Image Recognition”, 2015 Available online

Спасибо!

education