Lecture 13

Introduction to Convolutional Neural Networks

Part 3

STAT 479: Deep Learning, Spring 2019

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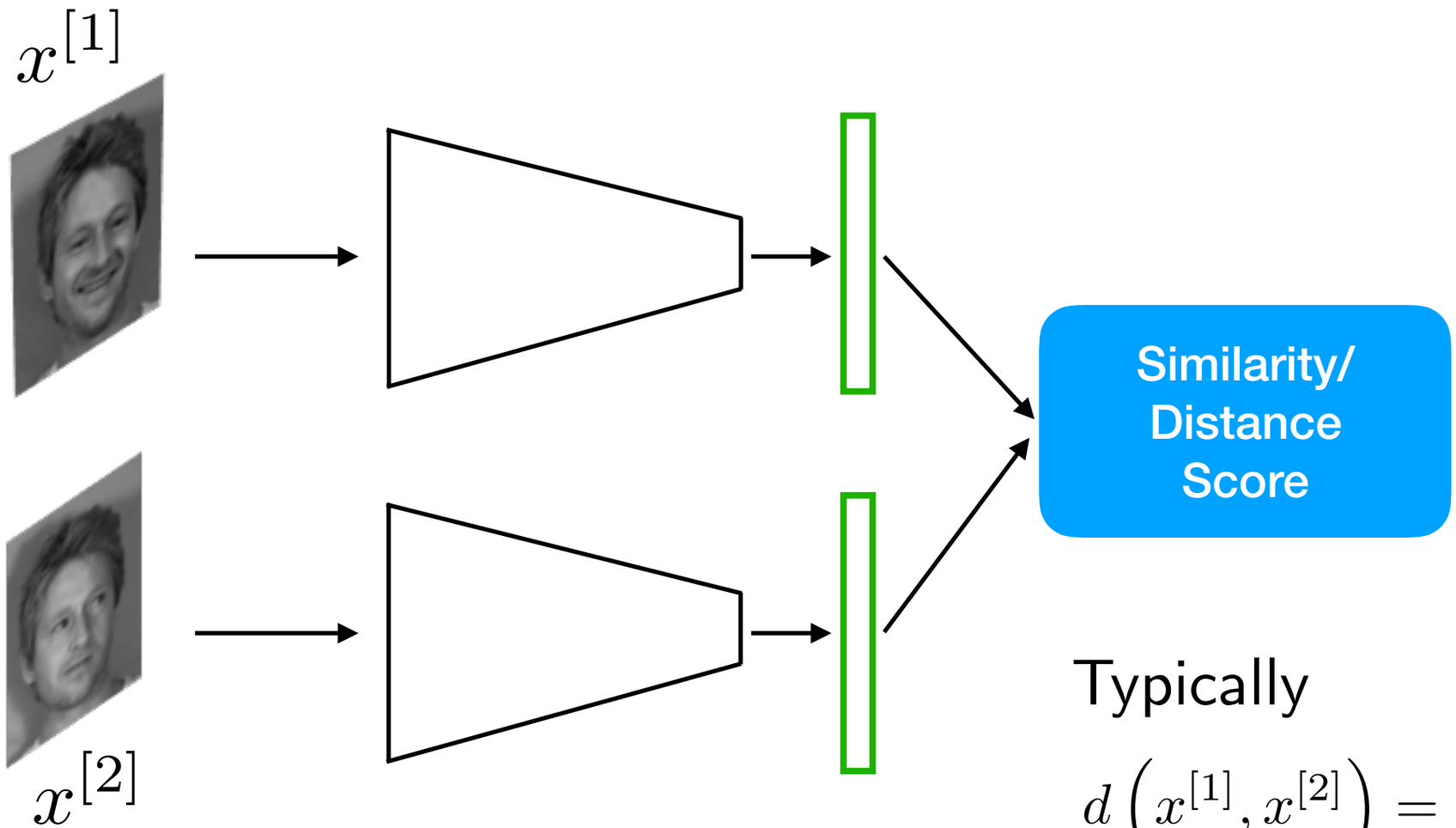
http://stat.wisc.edu/~sraschka/teaching/stat479-ss2019/

Face Recognition and Metric Learning

Siamese Networks



Typically

$$d\left(x^{[1]}, x^{[2]}\right) = \left|\left|f\left(x^{[1]}\right) - f\left(x^{[1]}\right)\right|\right|_2^2$$

or

$$d\left(x^{[1]}, x^{[2]}\right) = \left|f\left(x^{[1]}\right) - f\left(x^{[1]}\right)\right|_1$$

Siamese Networks

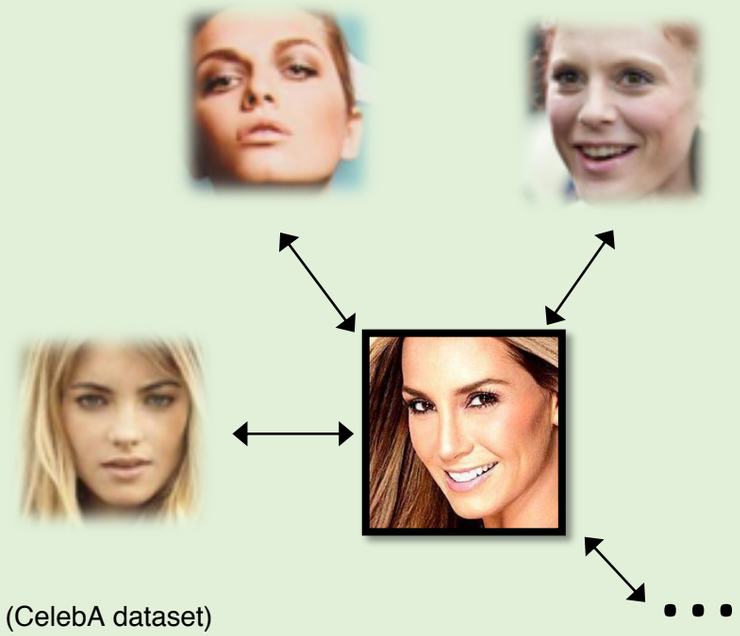
Often used for "One-shot learning"

- Suppose you trained a Siamese network for verification tasks
- Now, suppose you have only ~1 object per class
- You can compare any new object to any object based on maximum similarity to your given images (somewhat related to K-nearest neighbors)

Face Recognition:
Face Identification vs Face Verification

A. Identification

Determine identity of an unknown person
1-to-*n* matching

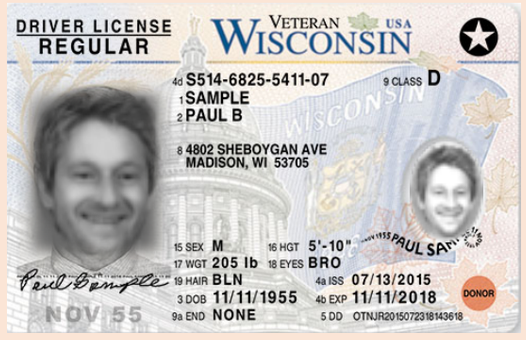


(CelebA dataset)

dataset link: http://mmlab.ie.cuhk.edu.hk/projects/CelebA.html

B. Verification

Verify claimed identity of a person
1-to-1 matching



(MUCT dataset)

dataset link: http://www.milbo.org/muct/

DeepFace

Taigman, Yaniv, Ming Yang, Marc'Aurelio Ranzato, and Lior Wolf. "Deepface: Closing the gap to human-level performance in face verification." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1701-1708. 2014.

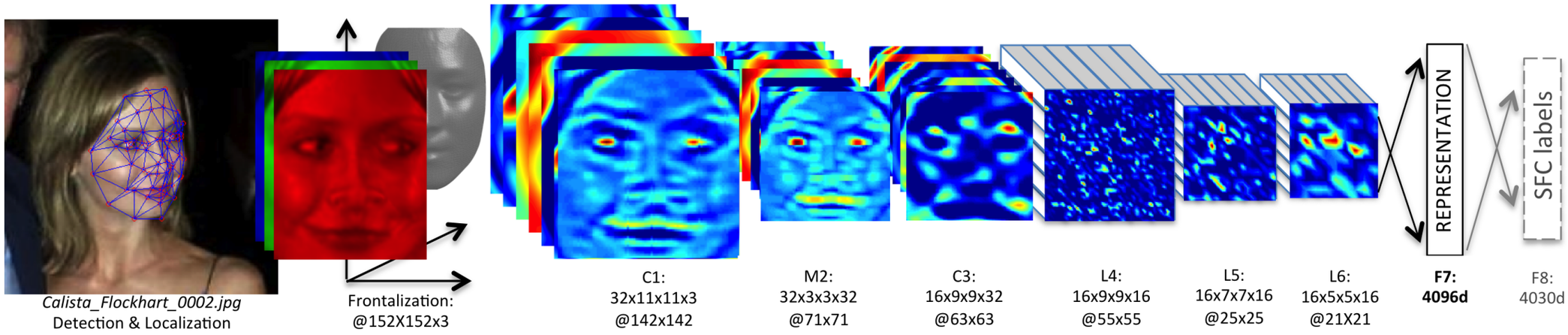
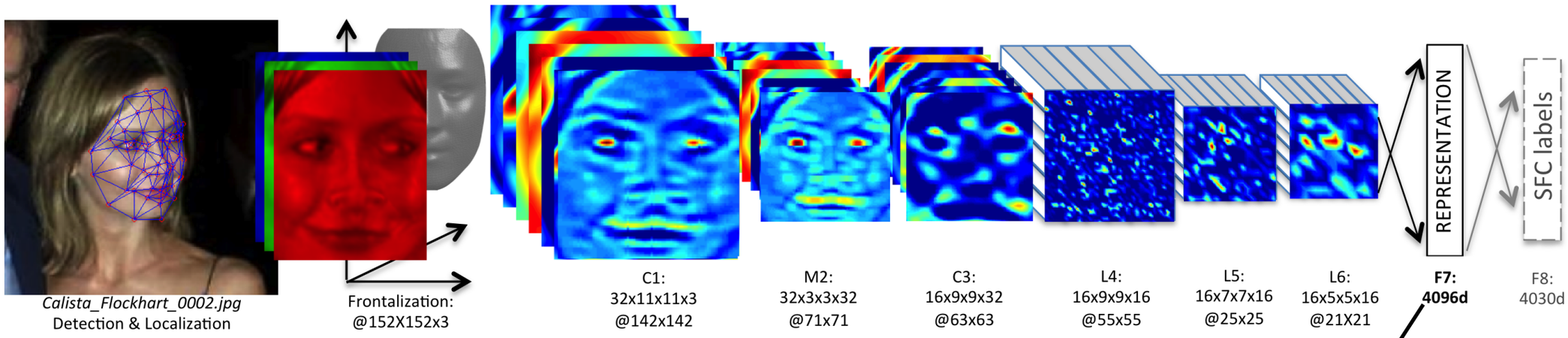


Figure 2. **Outline of the *DeepFace* architecture**. A front-end of a single convolution-pooling-convolution filtering on the rectified input, followed by three locally-connected layers and two fully-connected layers. Colors illustrate feature maps produced at each layer. The net includes more than 120 million parameters, where more than 95% come from the local and fully connected layers.

Hybrid between traditional methods and deep learning

DeepFace

Taigman, Yaniv, Ming Yang, Marc'Aurelio Ranzato, and Lior Wolf. "Deepface: Closing the gap to human-level performance in face verification." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1701-1708. 2014.



Given an image I, the representation $G(I)$ is then computed using the described feed-forward network. Any feed-forward neural network with L layers, can be seen as a composition of functions g^l_ϕ. In our case, the representation is: $G(I) = g^{F_7}_\phi(g^{L_6}_\phi(...g^{C_1}_\phi(T(I, \theta_T))...))$ with the net's parameters $\phi = \{C_1, ..., F_7\}$ and $\theta_T = \{x_{2d}, \vec{P}, \vec{r}\}$ as described in Section 2.

Normaliaztion As a final stage we normalize the features to be between zero and one in order to reduce the sensitivity to illumination changes: Each component of the feature vector is divided by its largest value across the training set. This is then followed by L_2-normalization: $f(I) := \bar{G}(I)/||\bar{G}(I)||_2$ where $\bar{G}(I)_i = G(I)_i / \max(G_i, \epsilon)$ [3]. Since we employ ReLU activations, our system is not invariant to re-scaling of the image intensities. Without bi-

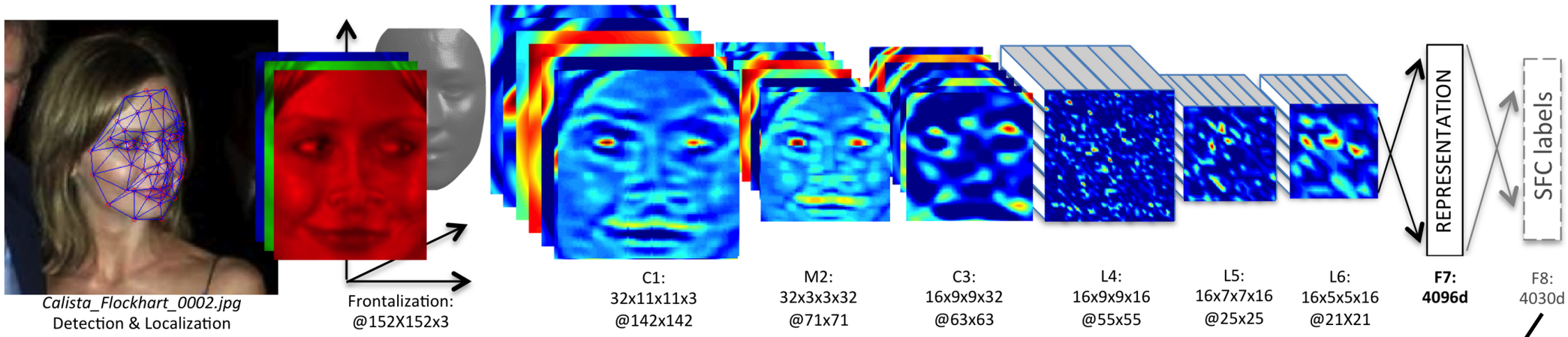
[2] See the **supplementary** material for more details.

[3] $\epsilon = 0.05$ in order to avoid division by a small number.

normalized feature vectors

DeepFace - Face Recognition

Taigman, Yaniv, Ming Yang, Marc'Aurelio Ranzato, and Lior Wolf. "Deepface: Closing the gap to human-level performance in face verification." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1701-1708. 2014.

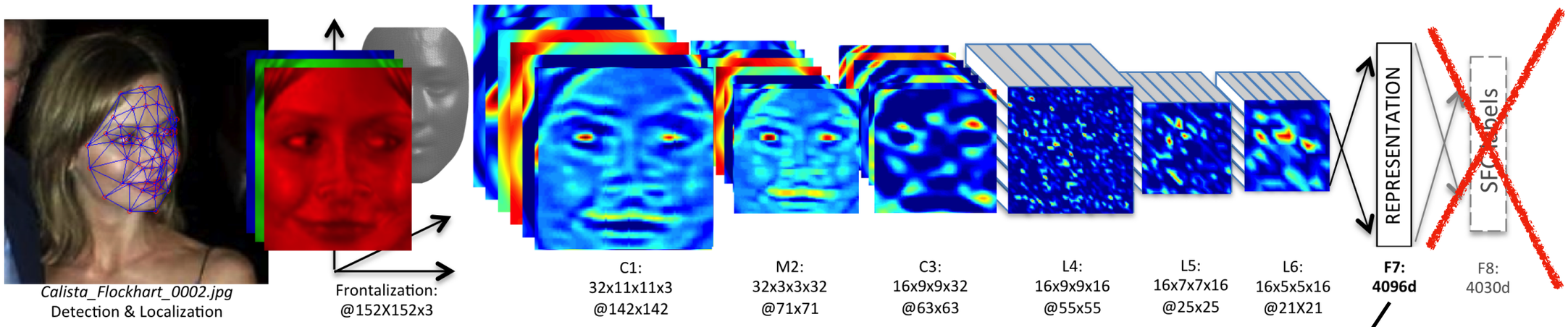


Regular softmax ouput layer for classifying faces (face IDs) optimized via cross-entropy loss.

Note they have 1-4k classes (they achieved a classification accuracy of ~93%).

DeepFace - Face Verification

Taigman, Yaniv, Ming Yang, Marc'Aurelio Ranzato, and Lior Wolf. "Deepface: Closing the gap to human-level performance in face verification." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1701-1708. 2014.



Weighted chi-square distance + SVM classifier for binary classification (predict whether two images depict the same person)

$$\chi^2\left(f_1, f_2\right) = \sum_i w_i \left(f_1[i] - f_2[i]\right)^2 / \left(f_1[i] + f_2[i]\right)$$

You may know this from other stats classes for comparing discrete probability distributions (histograms)

The weight is learned by the SVM.
(They achieved a classification accuracy is ~97%.)

FaceNet - Face Verification

Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 815-823. 2015.

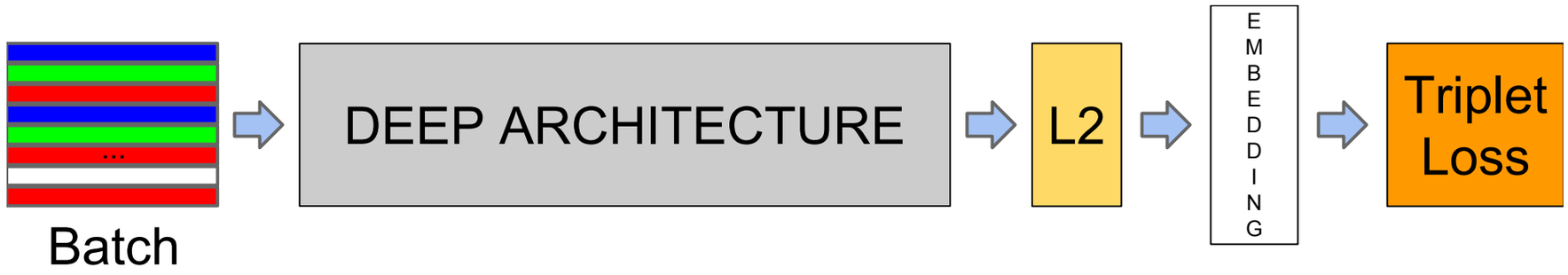
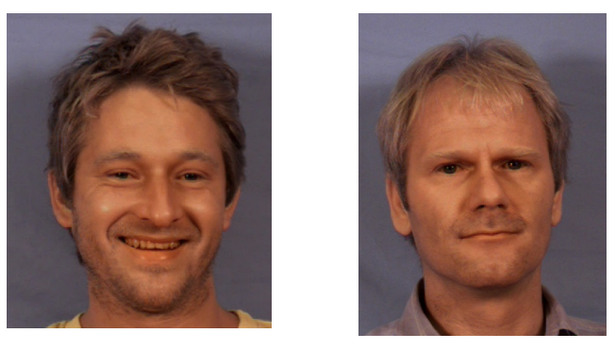


Figure 2. **Model structure.** Our network consists of a batch input layer and a deep CNN followed by L_2 normalization, which results in the face embedding. This is followed by the triplet loss during training.

Triplet Loss

Anchor Positive

Want encodings to be very similar
(small distance)



Anchor Negative

Want encodings to be very different
(large distance)

Triplet Loss

Anchor

Positive

Anchor

Negative

Want encodings to be very similar
(small distance)

Want encodings to be very different
(large distance)

$$d(A, P) \leq d(A, N)$$

$$\|f(A) - f(P)\|_2^2 \leq \|f(A) - f(N)\|_2^2$$

Triplet Loss

Anchor

Positive

Want encodings to be very similar
(small distance)

Anchor

Negative

Want encodings to be very different
(large distance)

$$d(A, P) + \alpha \leq d(A, N)$$

$$\|f(A) - f(P)\|_2^2 + \boxed{\alpha} \leq \|f(A) - f(N)\|_2^2$$

To make it a little harder

Triplet Loss

Anchor

Positive

Want encodings to be very similar
(small distance)

Anchor

Negative

Want encodings to be very different
(large distance)

$$d(A, P) + \alpha \leq d(A, N)$$

$$\|f(A) - f(P)\|_2^2 + \alpha \leq \|f(A) - f(N)\|_2^2$$

Rearrange

$$\|f(A) - f(P)\|_2^2 + \alpha - \|f(A) - f(N)\|_2^2 \leq 0$$

Triplet Loss

Anchor

Positive

Want encodings to be very similar
(small distance)

Anchor

Negative

Want encodings to be very different
(large distance)

Bounded loss function for training:

$$\mathcal{L}(A, P, N) = \max\left(\|f(A) - f(P)\|_2^2 + \alpha - \|f(A) - f(N)\|_2^2, 0\right)$$

Triplet Loss

Anchor

Positive

Want encodings to be very similar
(small distance)

Anchor

Negative

Want encodings to be very different
(large distance)

In practice: Selecting good pairs (those that are "hard")
is crucial during training

$$\mathcal{L}(A, P, N) = \max\left(\|f(A) - f(P)\|_2^2 + \alpha - \|f(A) - f(N)\|_2^2, 0\right)$$

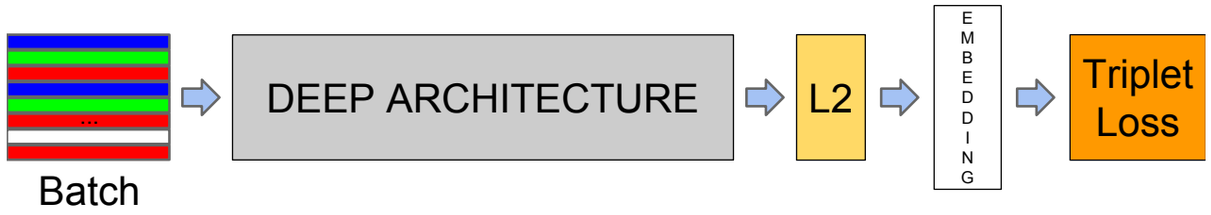


Figure 2. **Model structure.** Our network consists of a batch input layer and a deep CNN followed by L_2 normalization, which results in the face embedding. This is followed by the triplet loss during training.

Suppose we have 2 L2-normalized vectors:

$$\|\mathbf{x}\|_2 = \|\mathbf{y}\|_2 = 1$$

The squared L2 distance is then proportional to the cosine similarity

$$\begin{aligned}
\|\mathbf{x} - \mathbf{y}\|_2^2 &= (\mathbf{x} - \mathbf{y})^\top (\mathbf{x} - \mathbf{y}) \\
&= \mathbf{x}^\top \mathbf{x} - 2\mathbf{x}^\top \mathbf{y} + \mathbf{y}^\top \mathbf{y} \\
&= 2 - 2\mathbf{x}^\top \mathbf{y} \\
&= 2 - 2\cos(\mathbf{x}, \mathbf{y}) \qquad \text{where } \cos(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x}^\top \mathbf{y}}{\|\mathbf{x}\| \cdot \|\mathbf{y}\|} \in [-1, 1]
\end{aligned}$$

Optional: Recent Triplet Loss Variants

(not required), only for those who are interested

- Cosine Similarity-based triplet loss:

Li, Chao, Xiaokong Ma, Bing Jiang, Xiangang Li, Xuewei Zhang, Xiao Liu, Ying Cao, Ajay Kannan, and Zhenyao Zhu. "Deep speaker: an end-to-end neural speaker embedding system." *arXiv preprint arXiv:1705.02304* (2017).

- Angular Loss:

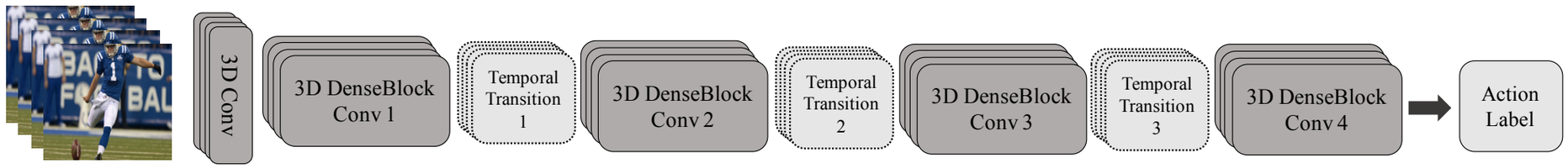
Wang, Jian, Feng Zhou, Shilei Wen, Xiao Liu, and Yuanqing Lin. "Deep metric learning with angular loss." In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 2593-2601. 2017.

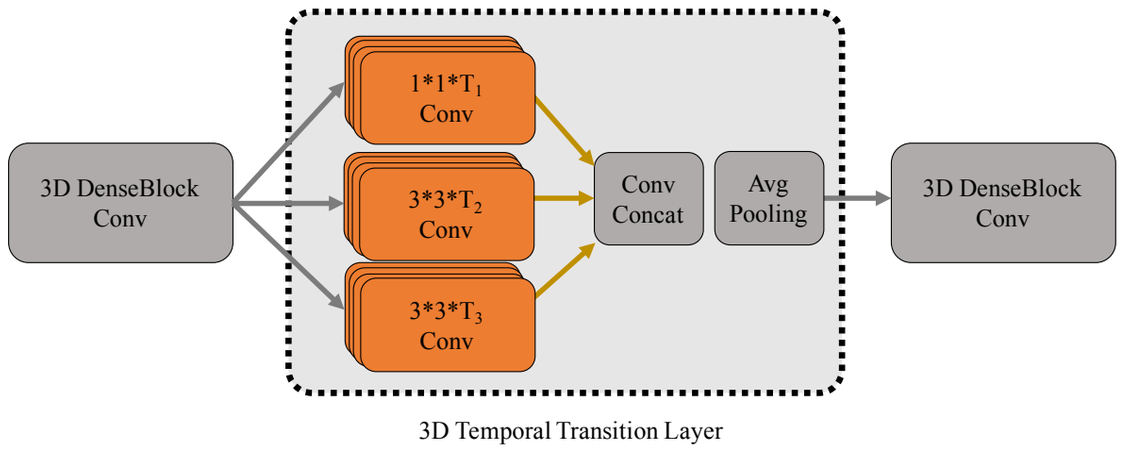
- Large margin cosine loss:

Wang, Hao, Yitong Wang, Zheng` Zhou, Xing Ji, Dihong Gong, Jingchao Zhou, Zhifeng Li, and Wei Liu. "Cosface: Large margin cosine loss for deep face recognition." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 5265-5274. 2018.

Additional Concepts to Wrap Up the Intro to Convolutional Neural Networks

ConvNets and 3D Inputs

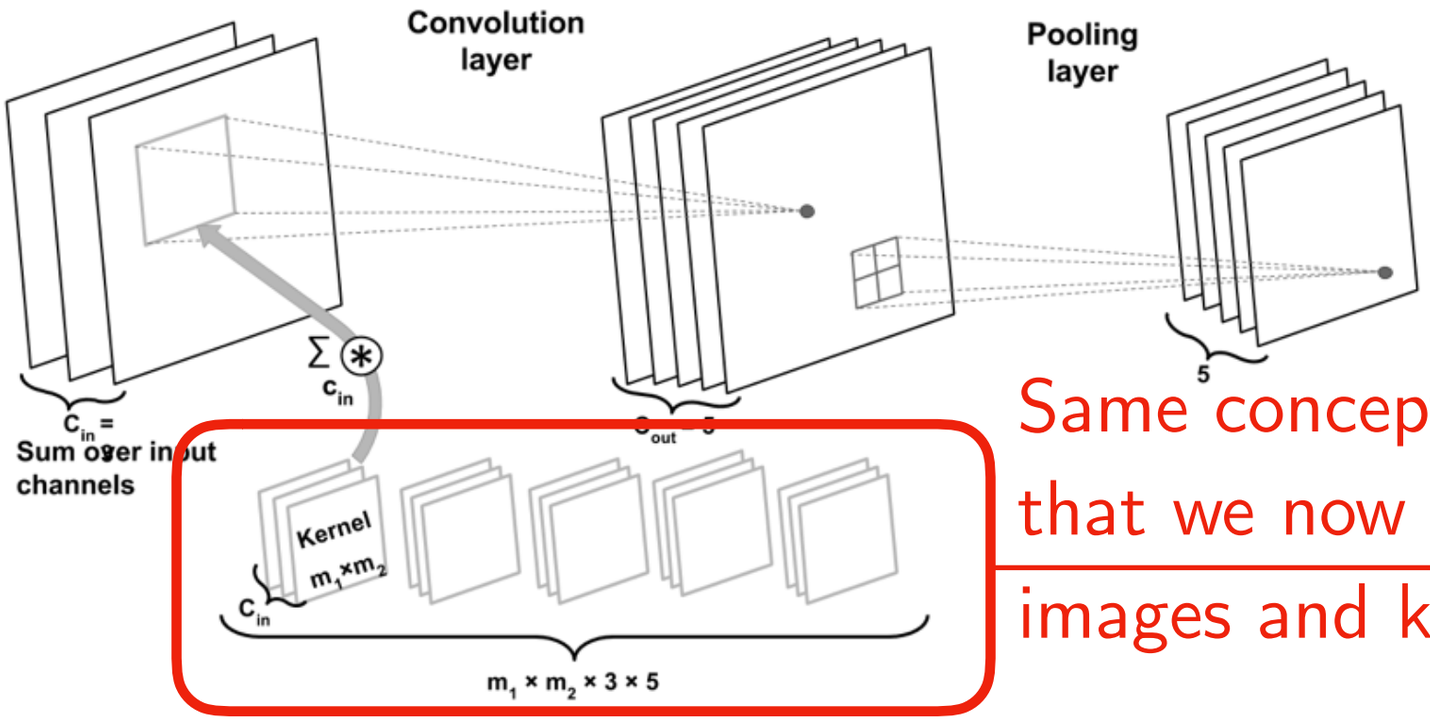




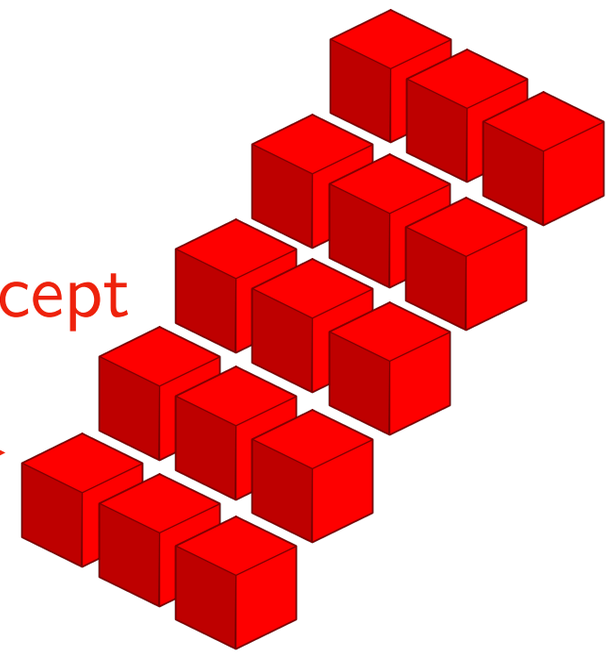
Diba, Ali, Mohsen Fayyaz, Vivek Sharma, Amir Hossein Karami, Mohammad Mahdi Arzani, Rahman Yousefzadeh, and Luc Van Gool. "Temporal 3d convnets: New architecture and transfer learning for video classification." *arXiv preprint arXiv: 1711.08200* (2017).

Also very popular for Medical Imaging (MRI, CT scans ...)

ConvNets and 3D Inputs



Same concept as before except that we now have 3D images and kernels



$$\mathbf{X} \in \mathbb{R}^{n_1 \times n_2 \times c_{in}}$$

$$\mathbf{W} \in \mathbb{R}^{m_1 \times m_2 \times c_{in} \times c_{out}} \quad \mathbf{b} \in \mathbb{R}^{c_{out}}$$

ConvNets and 3D Inputs

Usage is similar to Conv2d, except that we now have 3 dimensional kernels

Conv3d

CLASS `torch.nn.Conv3d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True)` [SOURCE]

Applies a 3D convolution over an input signal composed of several input planes.

https://pytorch.org/docs/stable/nn.html?highlight=conv3d#torch.nn.functional.conv3d

```
[1]: import torch
     import torch.nn as nn
```

```
[2]: m = nn.Conv3d(16, 33, 3, stride=2)
     m = nn.Conv3d(16, 33, (3, 5, 2), stride=(2, 1, 1), padding=(4, 2, 0))
     input = torch.randn(20, 16, 10, 50, 100)
     output = m(input)
```

```
[3]: input.size()
```

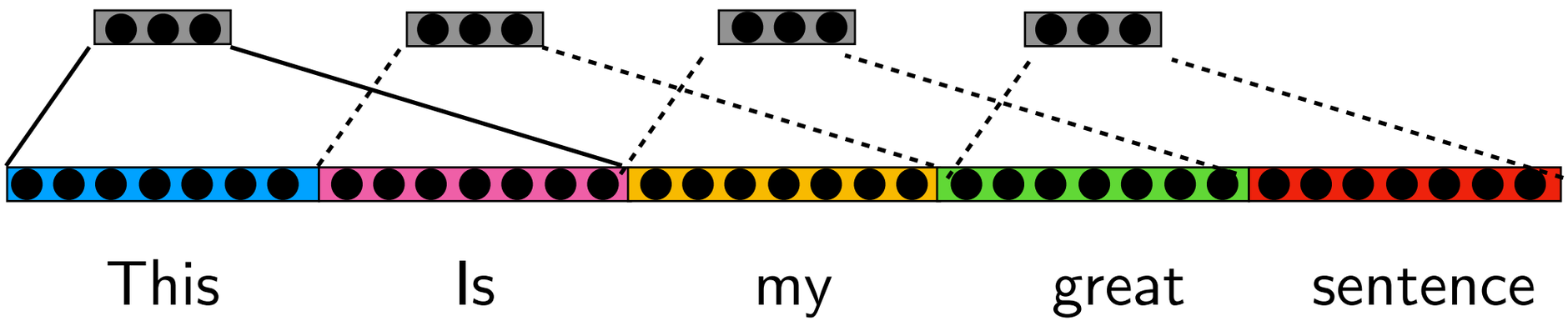
```
[3]: torch.Size([20, 16, 10, 50, 100])
```

```
[4]: output.size()
```

```
[4]: torch.Size([20, 33, 8, 50, 99])
```

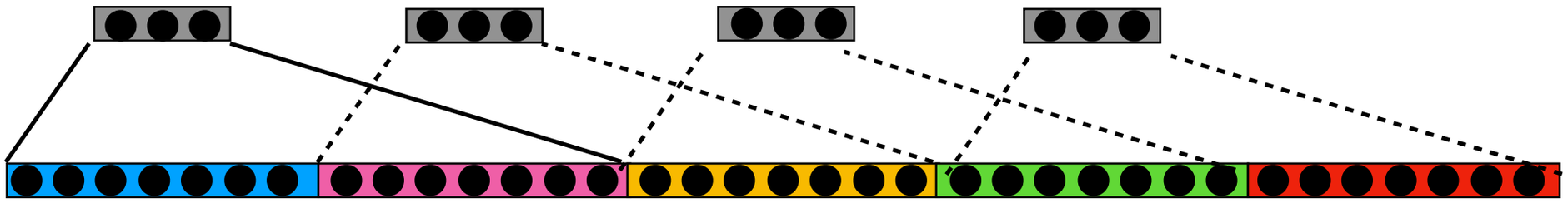
ConvNets for Text with 1D Convolutions

We can think of text as image with width 1



ConvNets for Text with 1D Convolutions

We can think of text as image with width 1



https://pytorch.org/docs/stable/nn.html#conv1d

Conv1d

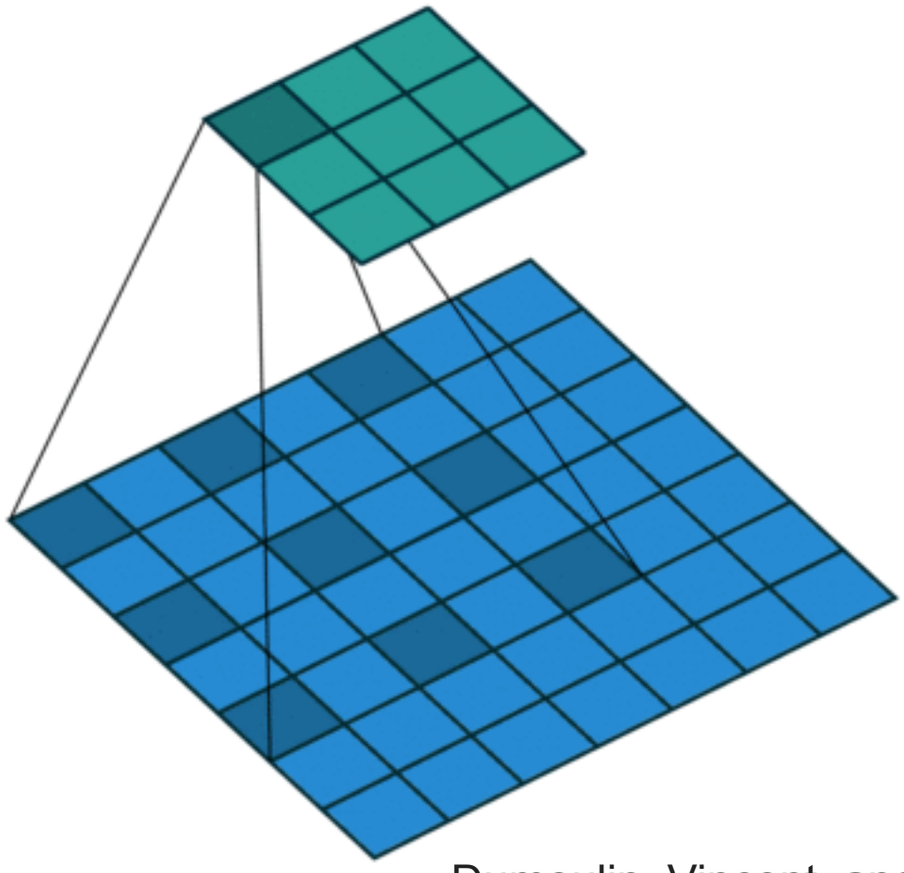
CLASS `torch.nn.Conv1d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True)` [SOURCE]

Applies a 1D convolution over an input signal composed of several input planes.

Dilated Convolutions

$$o = \left\lfloor \frac{i + 2p - k - (k-1)(d-1)}{s} \right\rfloor + 1$$

A 2-dilated 2D convolution



Dumoulin, Vincent, and Francesco Visin. "A guide to convolution arithmetic for deep learning." *arXiv preprint arXiv:1603.07285* (2016).

CNNs for Text (with 2D Convolutions)

Good results have also been achieved by representing a sentence as a matrix of word vectors and applying 2D convolutions (where each filter uses a different kernel size)

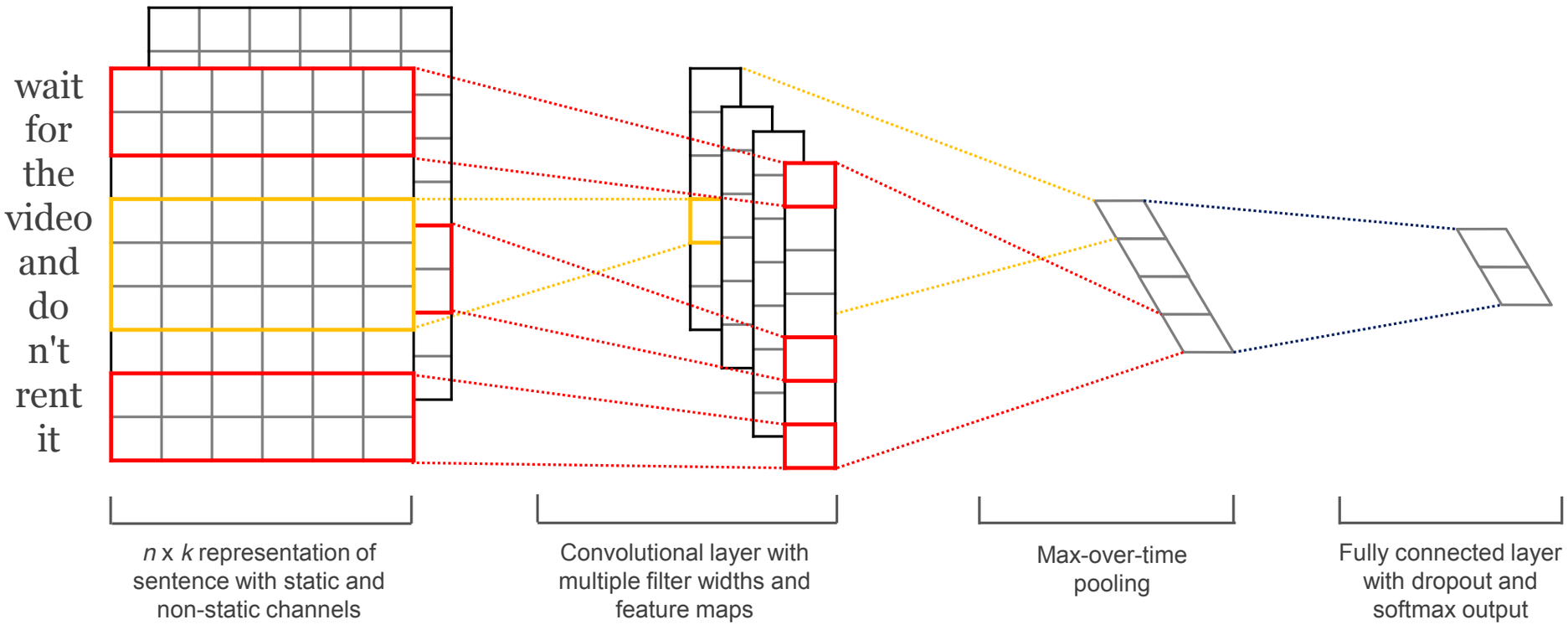


Figure 1: Model architecture with two channels for an example sentence.

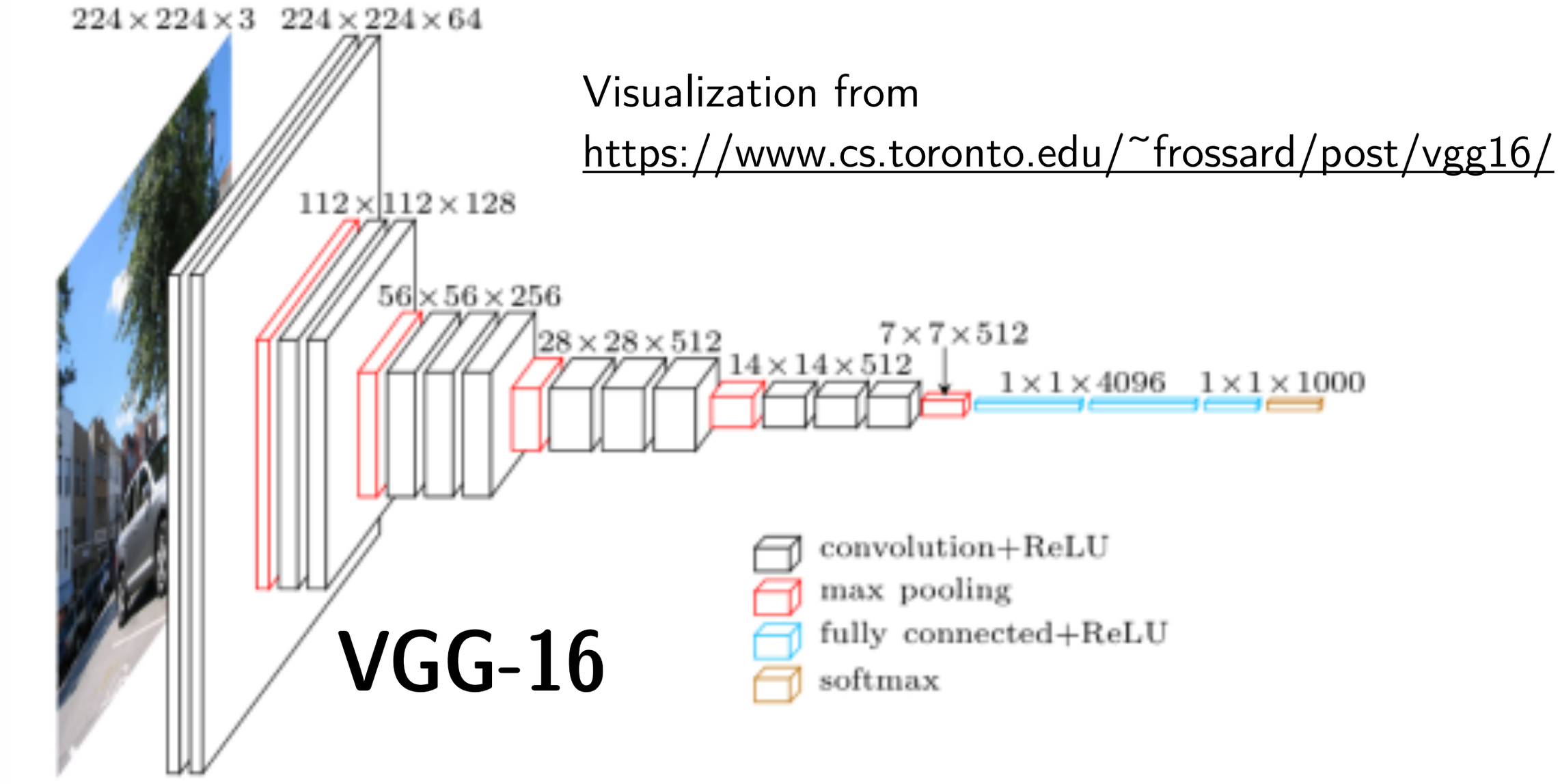
Kim, Y. (2014). Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*.

Transfer Learning

- A technique that may be useful for your class projects
- Key idea:
  - ✦ Feature extraction layers may be generally useful
  - ✦ Use a pre-trained model (e.g., pretrained on ImageNet)
  - ✦ Freeze the weights: Only train last layer (or last few layers)
- Related approach: Finetuning, train a pre-trained network on your smaller dataset

Transfer Learning

PyTorch implementation: https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/vgg16.ipynb

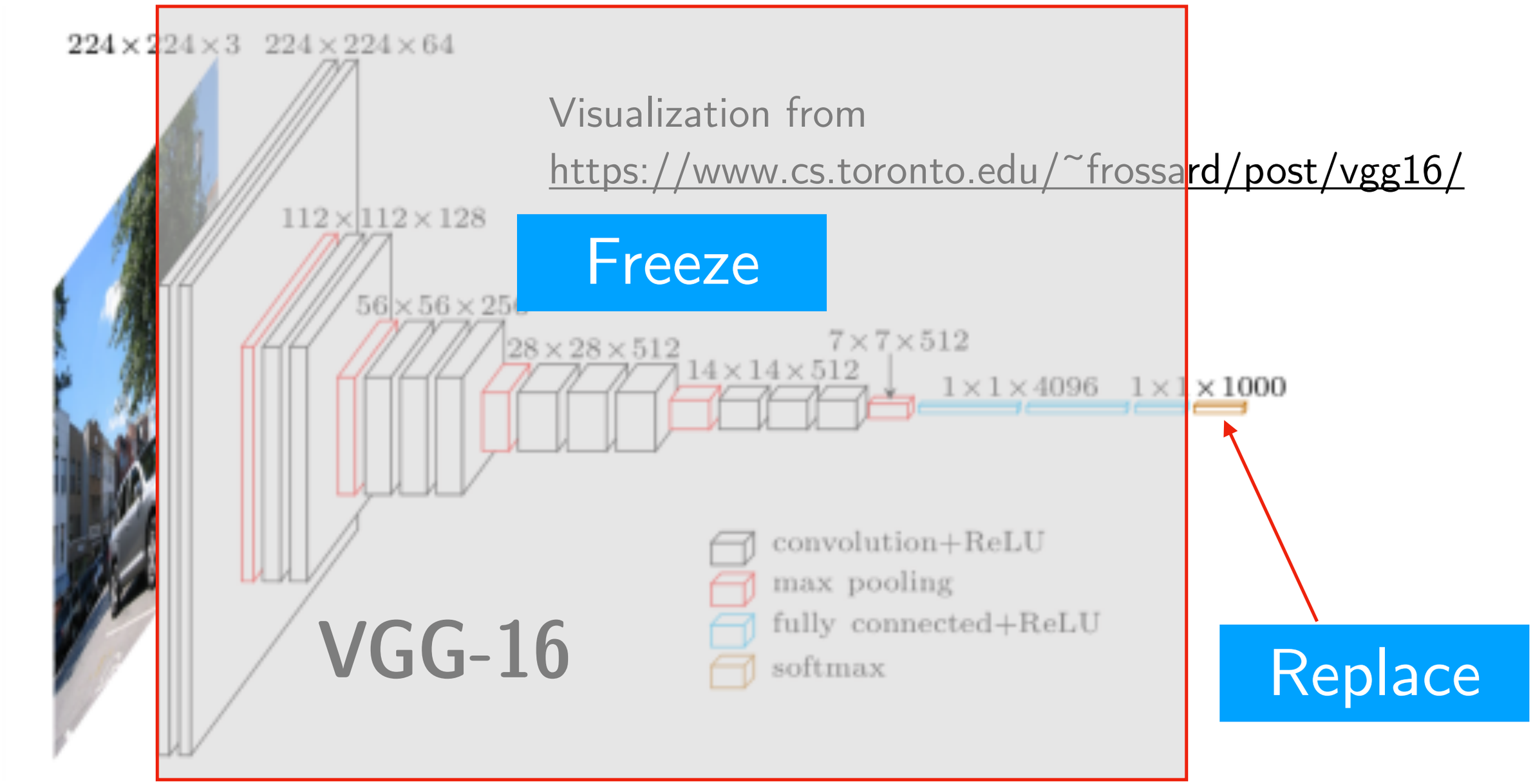


Visualization from
https://www.cs.toronto.edu/~frossard/post/vgg16/

Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).

Transfer Learning

PyTorch implementation: https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/vgg16.ipynb



Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).

Transfer Learning

https://pytorch.org/docs/stable/torchvision/models.html

Docs > torchvision > torchvision.models

TORCHVISION.MODELS

The models subpackage contains definitions for the following model architectures:

- AlexNet
- VGG
- ResNet
- SqueezeNet
- DenseNet
- Inception v3
- GoogLeNet

You can construct a model with random weights by calling its constructor:

```
import torchvision.models as models
resnet18 = models.resnet18()
alexnet = models.alexnet()
vgg16 = models.vgg16()
squeezenet = models.squeezenet1_0()
densenet = models.densenet161()
inception = models.inception_v3()
googlenet = models.googlenet()
```

Transfer Learning

https://pytorch.org/docs/stable/torchvision/models.html

Docs > torchvision > torchvision.models

TORCHVISION.MODELS

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All pre-trained models expect input images normalized in the same way, i.e. mini-batches of 3-channel RGB images of shape (3 x H x W), where H and W are expected to be at least 224. The images have to be loaded in to a range of [0, 1] and then normalized using `mean = [0.485, 0.456, 0.406]` and `std = [0.229, 0.224, 0.225]`. You can use the following transform to normalize:

```
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
```

Transfer Learning

PyTorch example: https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/vgg16-transferlearning.ipynb