Practical tutorial on deep neural networks and saliency detection: examples in speech recognition and singing bird detection

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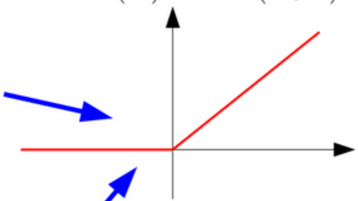
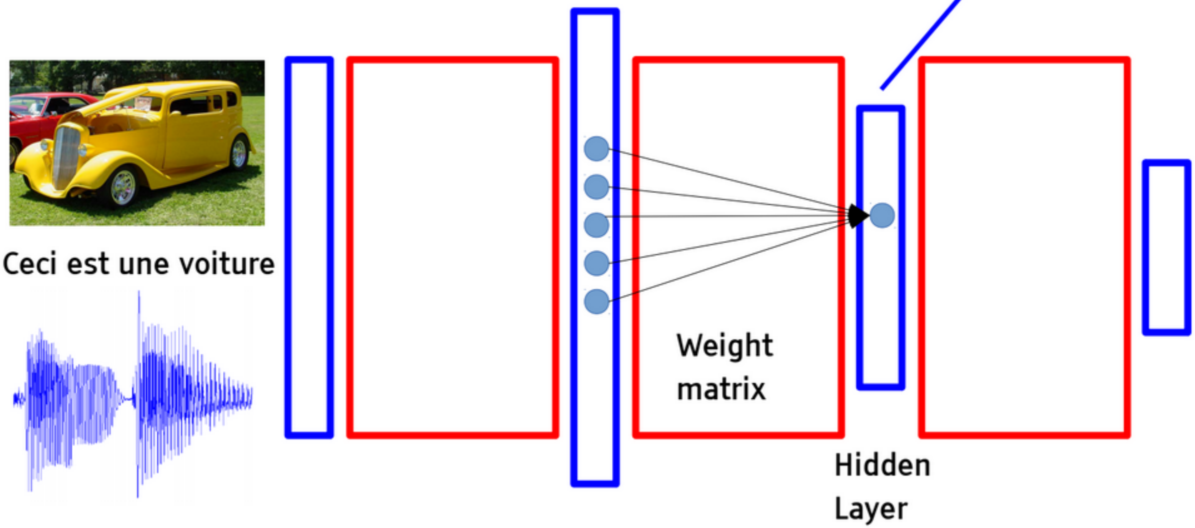
jDEV2017 - 6 juillet 2017 - Marseille

- Multiple Layers of **simple units**
- Each units computes a **weighted sum** of its inputs
- Weighted sum is passed through a **non-linear function**
- The learning algorithm changes the **weights**

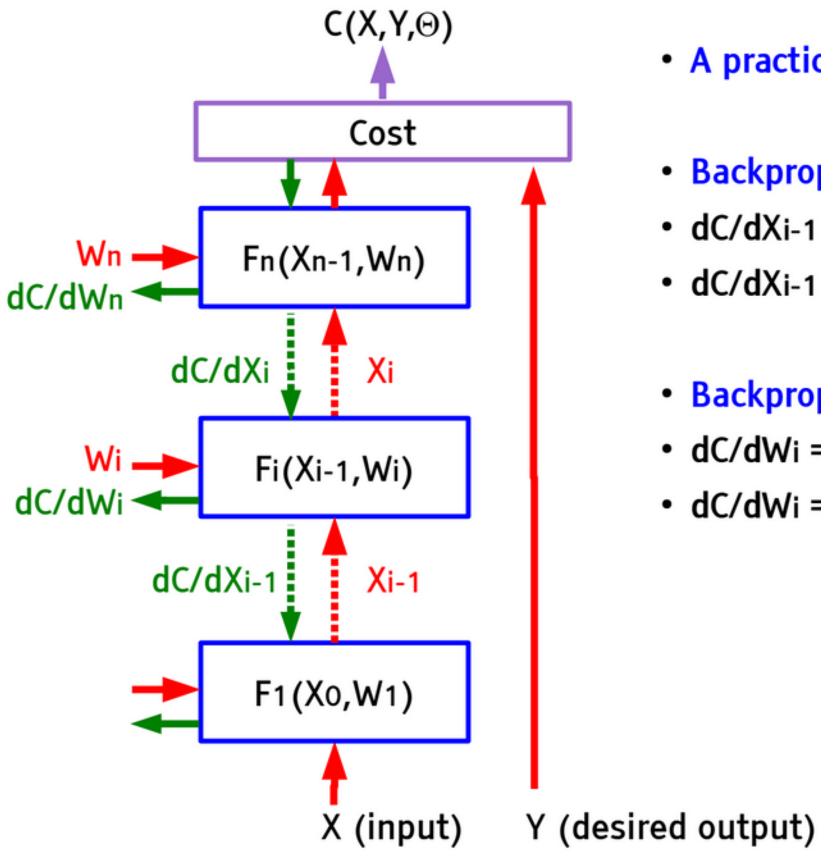
$$ReLU(x) = max(x, 0)$$





[Y. LeCun]

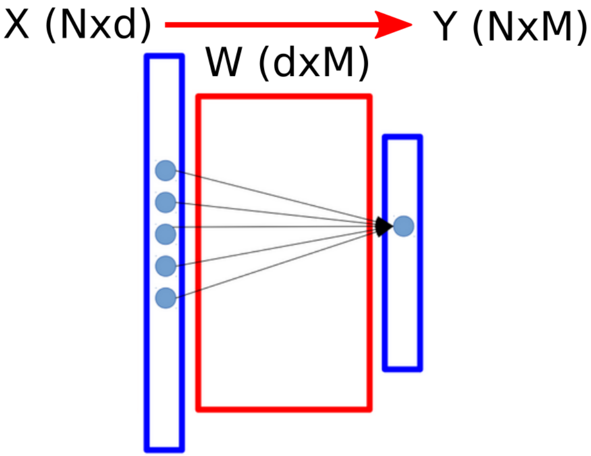
Gradients



- **A practical Application of Chain Rule**
- **Backprop for the state gradients:**
- $dC/dX_{i-1} = dC/dX_i \, . \, dX_i/dX_{i-1}$
- $dC/dX_{i-1} = dC/dX_i \, . \, dF_i(X_{i-1},W_i)/dX_{i-1}$
- **Backprop for the weight gradients:**
- $dC/dW_i = dC/dX_i \, . \, dX_i/dW_i$
- $dC/dW_i = dC/dX_i \, . \, dF_i(X_{i-1},W_i)/dW_i$

[Y. LeCun]

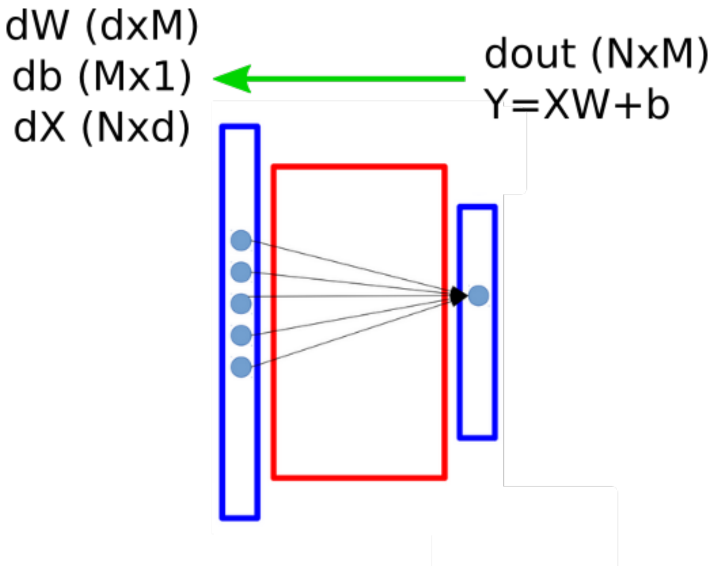
Affine layer: forward



$$Y = X \cdot W + b$$

```
def affine_forward(x, w, b):
  out = np.dot(x, w) + b
  cache = (x, w, b)
  return out, cache
```

Affine layer: backward



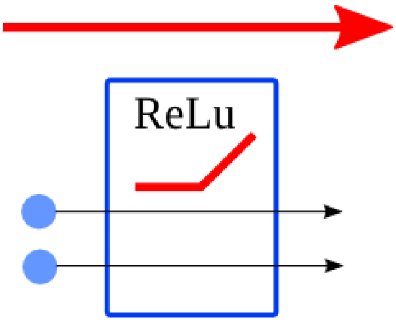
$$dW = X^t \cdot \mathrm{dout}$$

$$db = \sum_{i=1}^{N} \mathrm{dout}^{\mathrm{i}}$$

$$dx = \mathrm{dout} \cdot W^t$$

```
def affine_backward(dout, cache):
  x, w, b = cache
  dx = np.dot(dout, w.T)
  dw = np.dot(x.T, dout)
  db = np.sum(dout, axis=0)
  return dx, dw, db
```

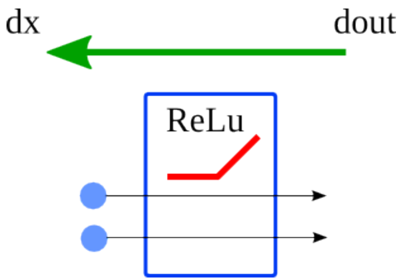
Non-linearity layer: ReLu forward



$$
\begin{aligned}
Y &= \max(0, X) \\
&= X * \mathbb{1}_{\{X>0\}} \\
&= X * [X > 0]
\end{aligned}
$$

```python
def relu_forward(x):
  out = np.maximum(np.zeros((x.shape)), x)
  cache = x
  return out, cache
```

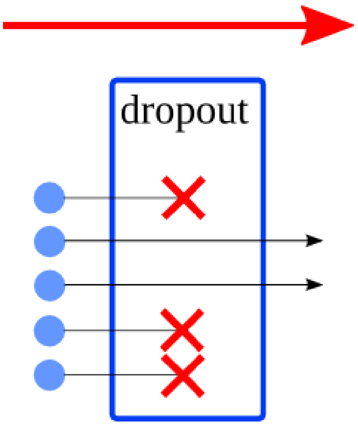
Non-linearity layer: ReLu backward



$$dx = [X > 0] * dout$$

```
def relu_backward(dout, cache):
  x = cache
  dx = dout * ((x>0)*1)
  return dx
```

Dropout layer: forward

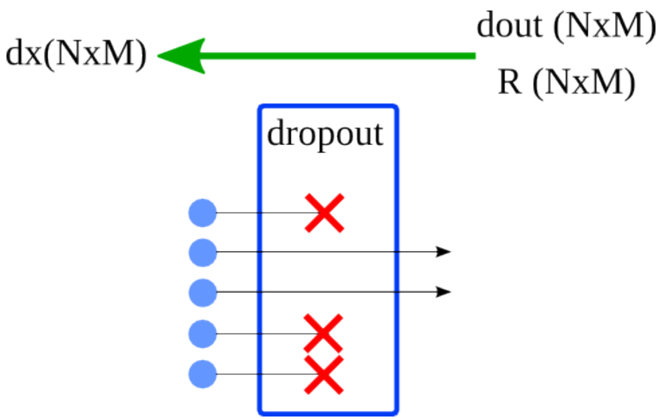


$$r_j \sim \text{bernoulli}(p)$$

$$Y = \mathbf{R} * X$$

```
def dropout_forward(x, p, mode):
  if mode == 'train':
    mask = (np.random.rand(*x.shape) < p) * 1
    out = x * mask
  elif mode == 'test':
    out = x
  cache = (p, mode, mask)
  out = out.astype(x.dtype, copy=False)
  return out, cache
```

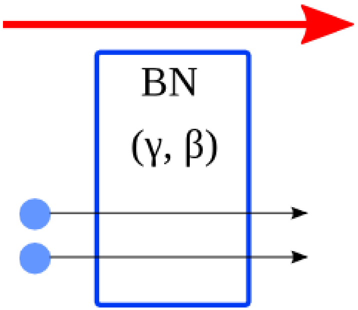
Dropout layer: backward



$$dx = \mathbf{R} * dout$$

```python
def dropout_backward(dout, cache):
  p, mode, mask = cache
  if mode == 'train':
    dx = dout * mask
  elif mode == 'test':
    dx = dout
  return dx
```

Batch-normalization layer



Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1 \ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

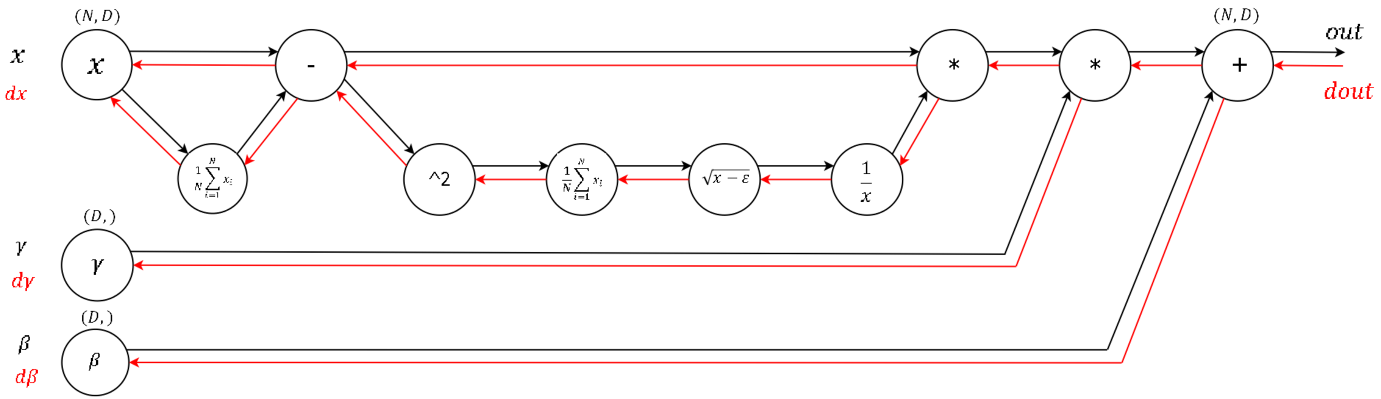
$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Batch-normalization layer



Batch-normalization layer: forward with running mean

```
def batchnorm_forward(x, gamma, beta, bn_param):
  mode = bn_param['mode']
  eps = bn_param.get('eps', 1e-5)
  momentum = bn_param.get('momentum', 0.9)

  N, D = x.shape
  running_mean = bn_param.get('running_mean', np.zeros(D, dtype=x.dtype))
  running_var = bn_param.get('running_var', np.zeros(D, dtype=x.dtype))

  if mode == 'train':
    moy = np.mean(x, axis=0)
    var = np.var(x, axis=0)
    num = x - moy
    den = np.sqrt(var + eps)
    x_hat = num / den
    out = gamma * x_hat + beta
    running_mean = momentum * running_mean + (1. - momentum) * moy
    running_var = momentum * running_var + (1. - momentum) * var
    cache = (x, gamma, beta, eps, moy, var, num, den, x_hat)
  elif mode == 'test':
    x_hat = (x - running_mean)/np.sqrt(running_var + eps)
    out = gamma * x_hat + beta
    cache = (x, gamma, beta)
  bn_param['running_mean'] = running_mean
  bn_param['running_var'] = running_var
  return out, cache
```

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Batch-normalization layer: backward with running mean

```python
def batchnorm_backward(dout, cache):
  x, gamma, beta, eps, moy, var, num, den, x_hat = cache
  dbeta = np.sum(dout, axis=0)
  dgamma = np.sum(dout*x_hat, axis=0)

  dxhat = gamma * dout
  dnum = dxhat / den
  dden = np.sum(-1.0 * num / (den**2) * dxhat, axis=0)

  dmu = np.sum(-1.0 * dnum, axis=0)
  dvareps = 1.0 / (2 * np.sqrt(var + eps)) * dden

  N, D = x.shape
  dx = 1.0 / N * dmu + 2.0 / N * (x - moy) * dvareps + dnum

  return dx, dgamma, dbeta
```

From scores to probabilities

$$\text{scores: } \mathbf{f} = F_n(X_{n-1}, W_n)$$

Probability associated to a given class k:

$$P(y = k | W, \mathbf{X}) = \frac{\exp(f_k)}{\sum_{j=0}^{C-1} \exp(f_j)} = \mathrm{softmax}(\mathbf{f}, k)$$

```python
def softmax(z):
  '''z: a vector or a matrix z of dim C x N '''
  z = z-np.max(z) # to avoid overflow with exp
  exp_z = np.exp(z)
  return exp_z / np.sum(exp_z, axis=0)
```

Categorical cross-entropy loss

$$\mathcal{L}(W) = -\frac{1}{N}\sum_{i=1}^{N}\mathcal{L}(W|y^i, \mathbf{x^i})$$

$$\mathcal{L}(W|y^i, \mathbf{x^i}) = -\log(P(y^i|W, \mathbf{x^i}))$$

Only the probability of the correct class is used in $\mathcal{L}$

Categorical cross-entropy loss: gradient

$$
\begin{aligned}
\nabla_{\mathbf{W_k}} \mathcal{L}(W|y^i, \mathbf{x^i}) &= \frac{\partial \mathcal{L}(W|y^i, \mathbf{x^i})}{\partial \mathbf{W_k}} \\
&= -\sum_{j=0}^{C-1} t_j^i \frac{\partial \log(z_j^i)}{\partial \mathbf{W_k}} \qquad \text{with } t_j^i = \mathbb{1}_{\{y^i = j\}} \\
&= -\sum_{j=0}^{C-1} t_j^i \frac{1}{z_j^i} \frac{\partial z_j^i}{\partial \mathbf{W_k}} \\
&= \dots \\
&= -\mathbf{x^i}(t_k^i - z_k^i) \\
&= \begin{cases} \mathbf{x^i}(z_k^i - 1) & \text{if } t_j^i = 1 \text{ (i.e., } y^i = k) \\ \mathbf{x^i} z_k^i & \text{if } t_j^i = 0 \text{ (i.e., } y^i \neq k) \end{cases}
\end{aligned}
$$

Categorical cross-entropy loss

```python
def softmax_loss_vectorized(W, X, y, reg):
  """
  Softmax loss function, vectorized version.
  Inputs: same as softmax_loss_naive
  """
  # Initialize the loss and gradient to zero.
  loss = 0.0
  dW = np.zeros_like(W)
  D, N = X.shape
  C, _ = W.shape

  probs = softmax(W.dot(X)) # dim: C, N
  probs = probs.T # dim: N, C
  # compute loss only with probs of the training targets
  loss = np.sum(-np.log(probs[range(N), y]))
  loss /= N
  loss += 0.5 * reg * np.sum(W**2)

  dW = probs # dim: N, C
  dW[range(N), y] -= 1
  dW = np.dot(dW.T, X.T)
  dW /= N
  dW += reg * np.sum(W)

  return loss, dW
```

Our first modern network!

```
def affine_BN_relu_dropout_forward(x, w, b, gamma,\
  beta, bn_param, p, mode):

  network, fc_cache = affine_forward(x, w, b)
  network, bn_cache = batchnorm_forward(network, \
  gamma, beta, bn_param)

  network, relu_cache = relu_forward(network)
  network, dp_cache = dropout_forward(network, p, \
  mode)

  cache = (fc_cache, bn_cache, relu_cache, dp_cache)

  return network, cache

def affine_BN_relu_dropout_backward(...):
  ...
```

Our first modern network! Easier with a toolbox...

```
from lasagne.layers import InputLayer, DenseLayer,
  NonlinearityLayer, BatchNormLayer, DropoutLayer
from lasagne.nonlinearities import softmax

net = {}
net['input'] = InputLayer((None, 3, 32, 32))
net['aff'] = DenseLayer(net['input'], \
                 num_units=1000, nonlinearity=None)
net['bn'] = BatchNormLayer(net['aff'])
net['relu'] = NonlinearityLayer(net['bn'])
net['dp'] = DropoutLayer(net['relu'])
net['prob'] = NonlinearityLayer(net['dp'], softmax)
```

Questions

- Which features are typically used as input?
- How to choose and design a model architecture?
- How to get a sense of what a model did learn?
- What is salient in the input that makes a model take a decision?

Examples in speech and singing birds

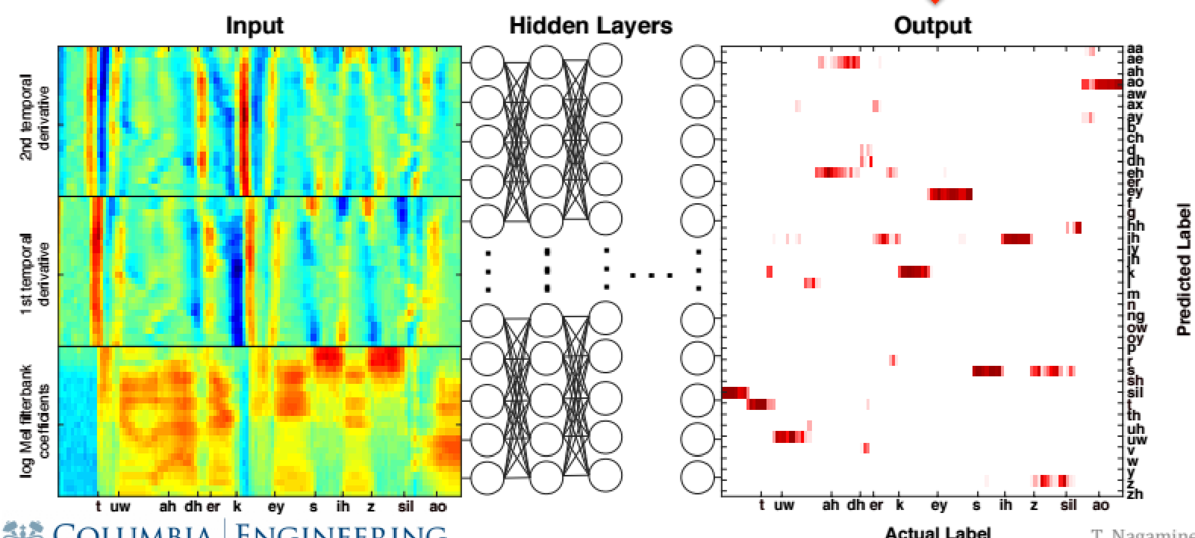
Phone recognition: DNN

DNN Architecture

Input layer
11 frames of 24-dimensional log Mel filter bank coefficients + deltas

5 sigmoid hidden layers
256 nodes each; fully connected feed-forward

Softmax output layer
41 nodes for 40 phonemes and silence; context independent



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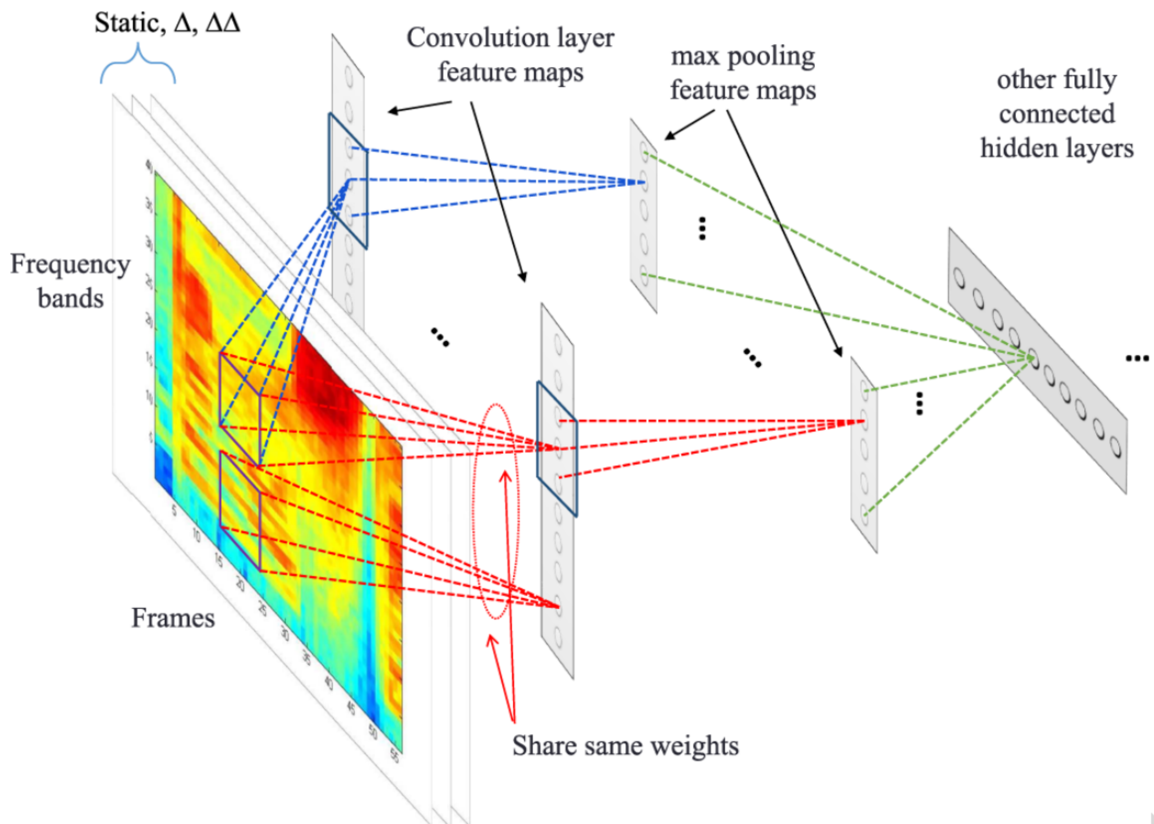
The Fu Foundation School of Engineering and Applied Science

T. Nagamine
INTERSPEECH 2015

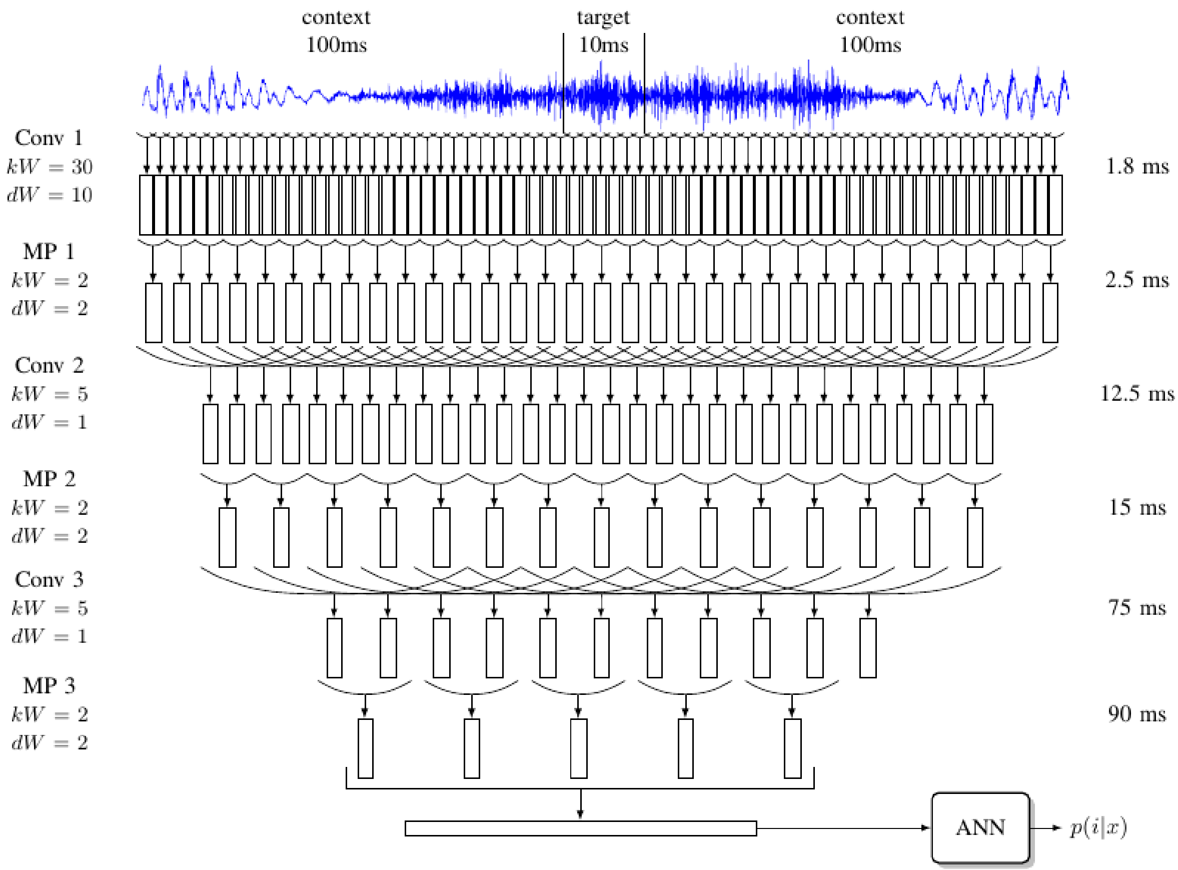
[Nagamine et al., IS 2015; Slide by T. Nagamine]

Phone recognition: CNN



[Abdel-Hamid et al., TASLP 2014]

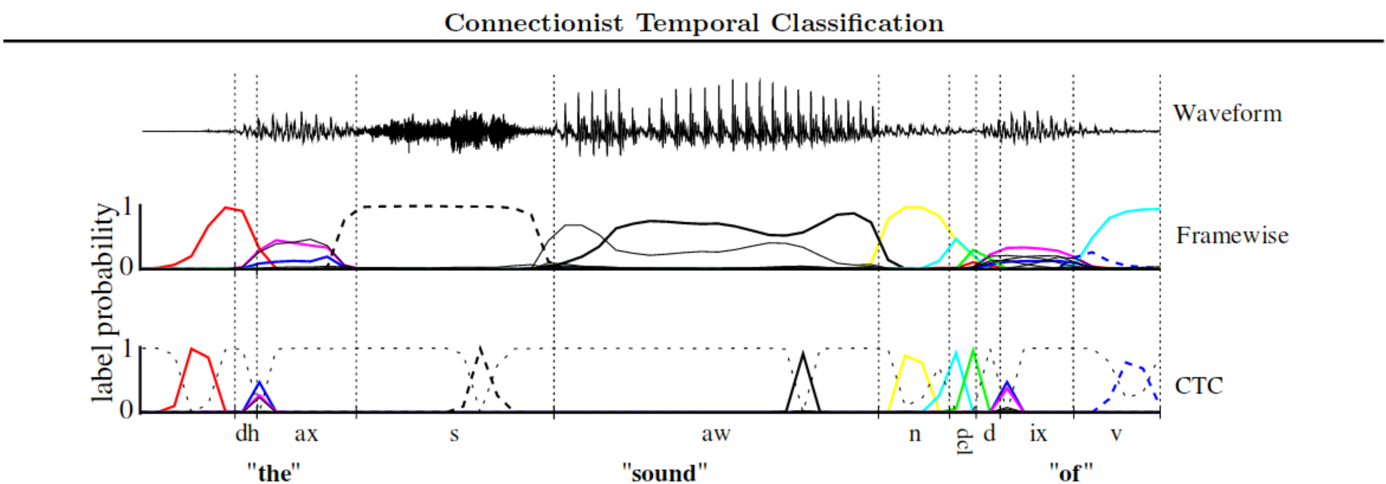
Phone recognition: CNN with raw speech



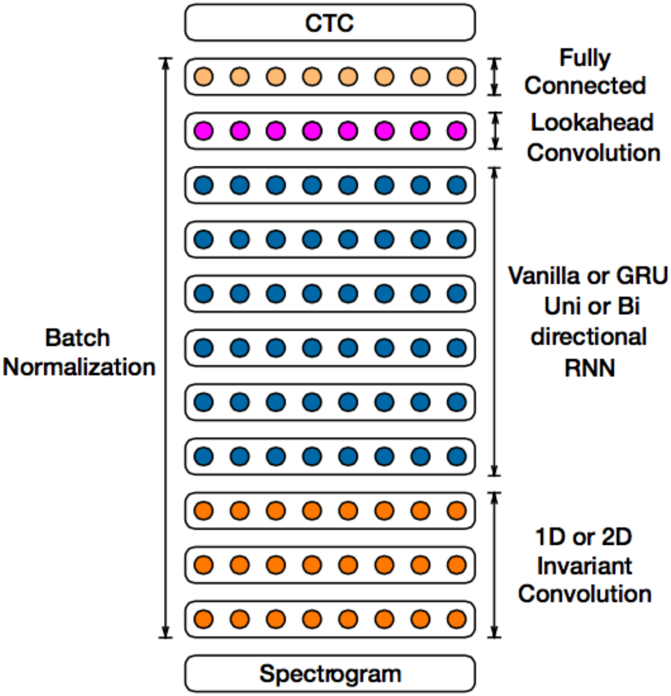
[Magimai-Doss et al., IS 2013 ; Slide by M. Magimai-Doss]

Handling time series

- Frame with context: decision at frame-level
- Pre-segmented sequences: TDNN, RNN, LSTM
- Sequences with no previous segmentation : Connectionist Temporal Classification loss [Graves, ICML 2006]



Phone recognition: CNN+RNN "deepspeech2"



[D. Amodei et al. "Deep speech 2: End-to-end speech recognition in english and mandarin." International Conference on Machine Learning. 2016.]

Recent convNets architectures

- Standard convNets

$$x_i = F_i(x_{i-1})$$


WE NEED TO GO
DEEPER

Recent convNets architectures

- Standard convNets

$$x_i = F_i(x_{i-1})$$

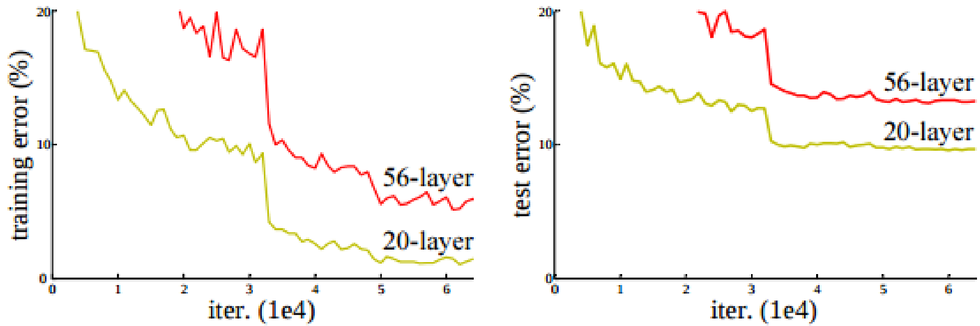


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

[He *et al*, CVPR 2016]

Recent convNets architectures

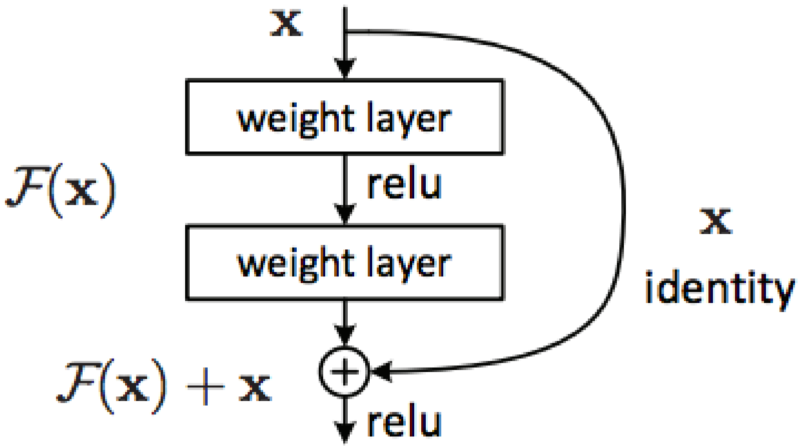
- Standard convNets [LeCun, 1995]

$$x_i = F_i(x_{i-1})$$

- Residual convNets [He *et al*, CVPR 2016]

$$x_i = F_i(x_{i-1}) + x_{i-1}$$

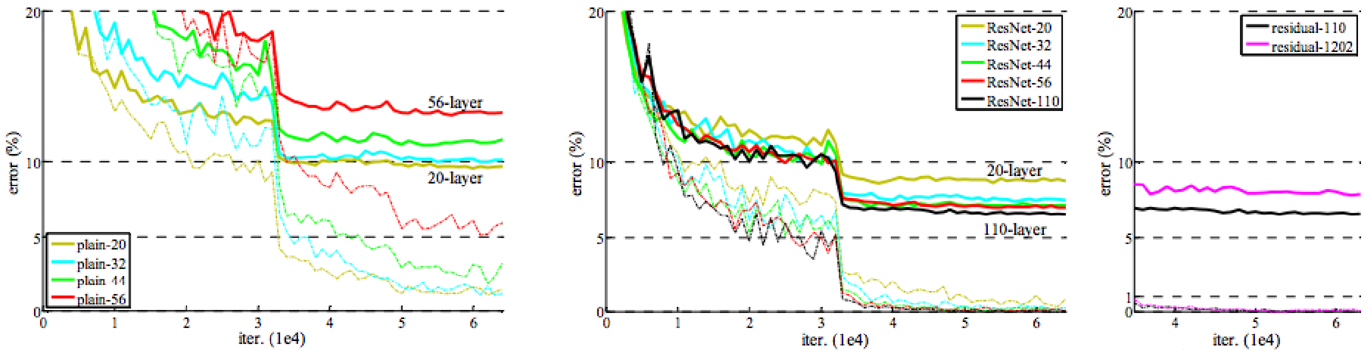
Residual convNets: resNets



- 152-layer resNet: 3.57% top-5 error on ImageNet (ensemble)

[He *et al*, CVPR 2016]

Residual convNets: resNets



[He *et al*, CVPR 2016]

Recent convNets architectures

- Standard convNets [LeCun, 1995]

$$x_i = F_i(x_{i-1})$$

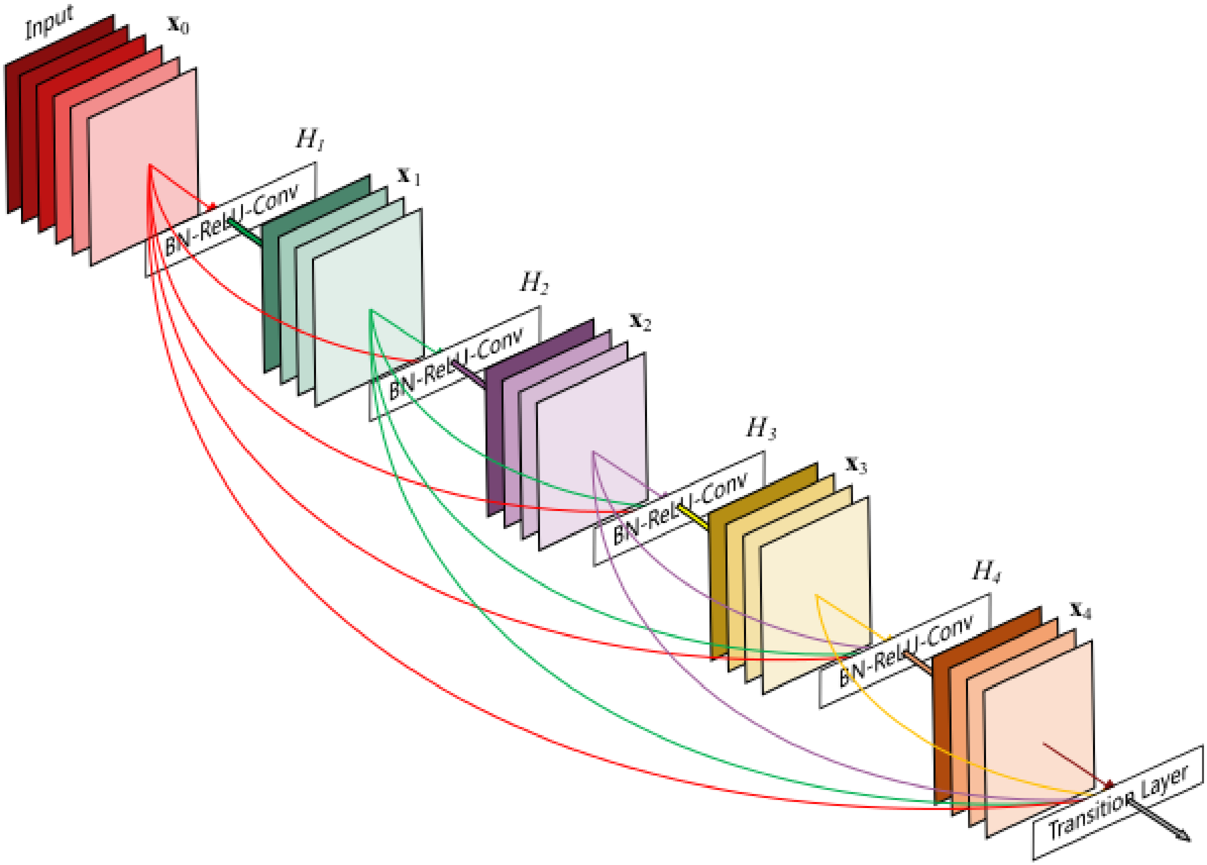
- Residual convNets [He *et al*, CVPR 2016]

$$x_i = F_i(x_{i-1}) + x_{i-1}$$

- Densely connected convNets [Huang *et al*, 2016]

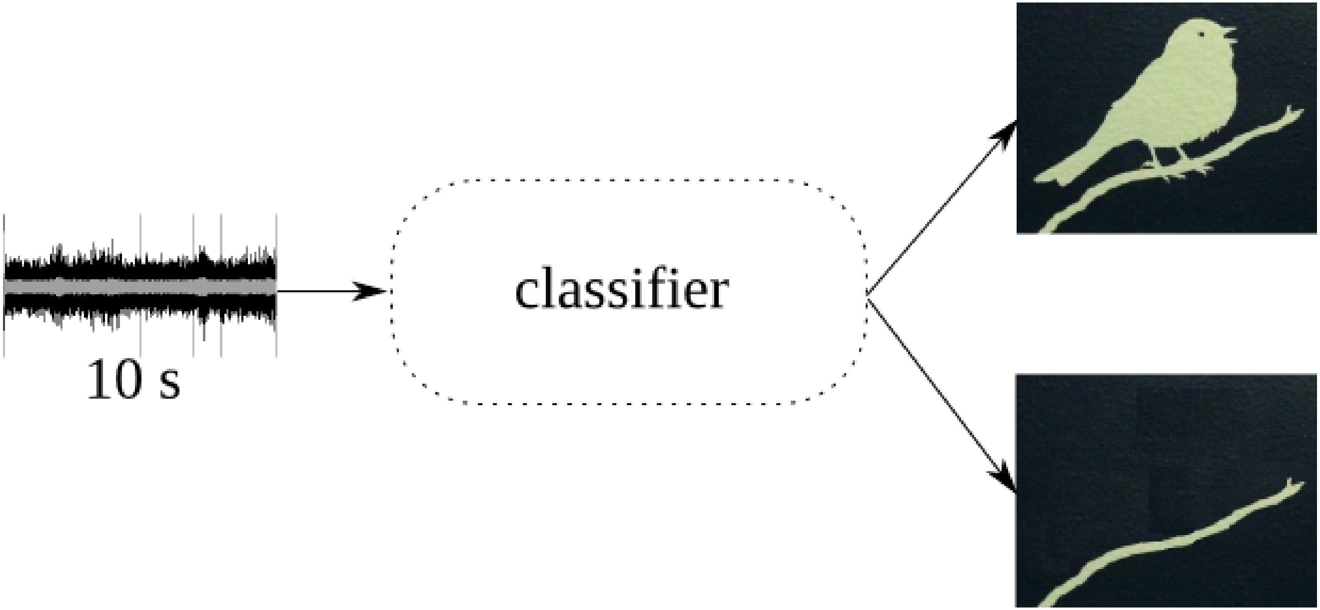
$$x_i = F_i([x_0, x_1, \ldots, x_{i-1}])$$

DenseNets: dense blocks



He *et al*, CVPR 2016

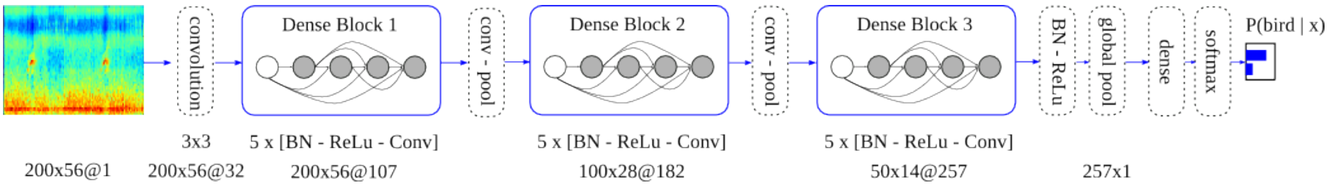
Bird Audio Detection challenge 2017



Bird Audio Detection challenge 2017

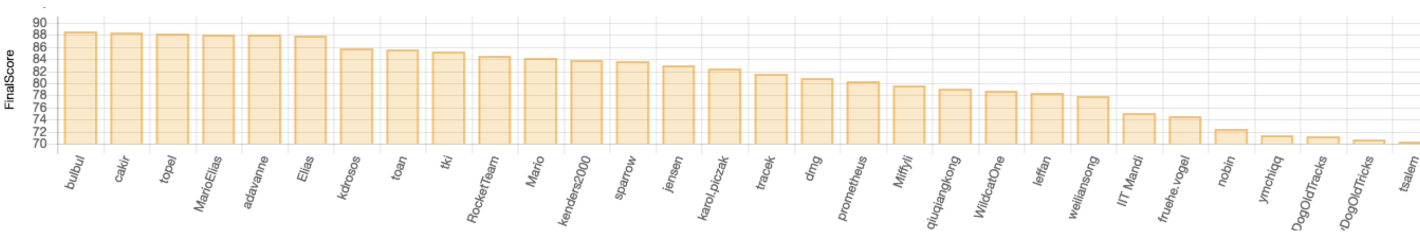
	Train	Valid	Test
Freefield1010	6,152	384	1,154
Warblr	6,800	500	700
Merged	14,806	884	0
Tchernobyl	_	_	8,620

Proposed solution: denseNets



- 74 layers
- 328k parameters

Proposed solution: denseNets



Rank	User	Info	Preview Score	Final Score
1	bulbul		88.9 %	88.7 %
2	cakir		88.3 %	88.5 %
3	topel		88.8 %	88.2 %
4	MarioElias		88.5 %	88.1 %
5	adavanne		88.2 %	88.1 %
6	Elias		88.0 %	88.0 %
7	kdrosos		86.1 %	85.8 %

- Code densenet + saliency:

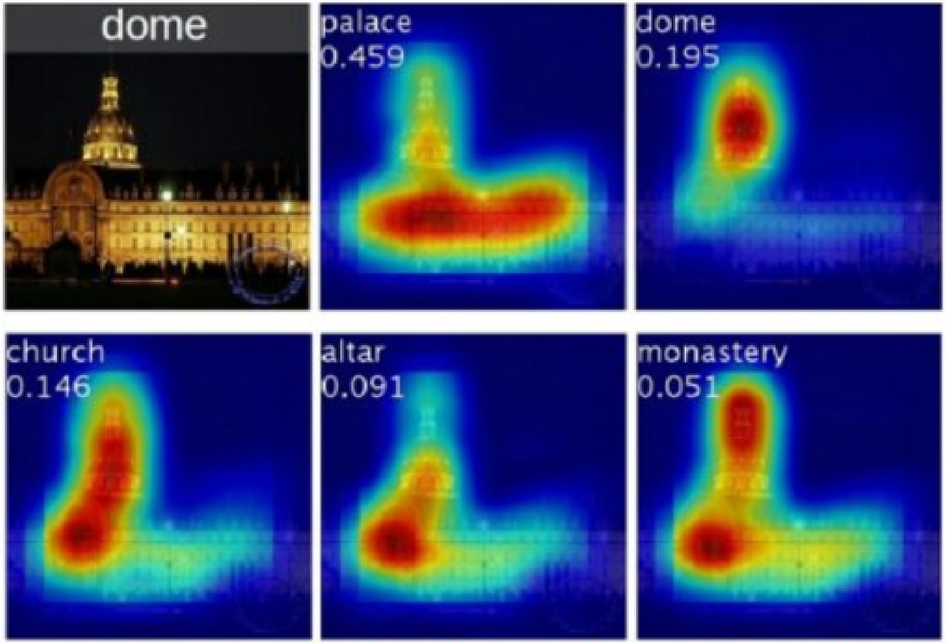
  https://github.com/topel/
- Audio + saliency map examples:

  https://goo.gl/chxOPD

How to get a sense of what a model did learn?

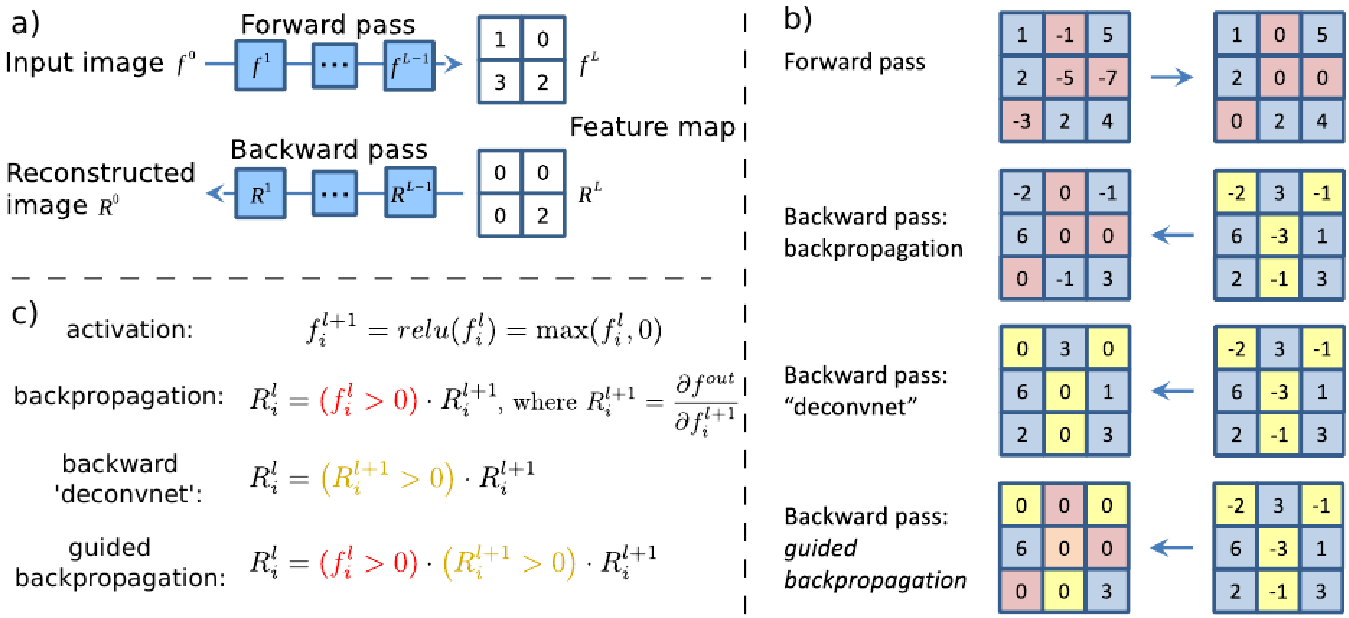
- Analysis of the weights (plotting), activation maps
- Saliency maps: which input elements (e.g., which pixels in case of an input image) need to be changed the least to affect the prediction the most?

Class-specific Saliency Map



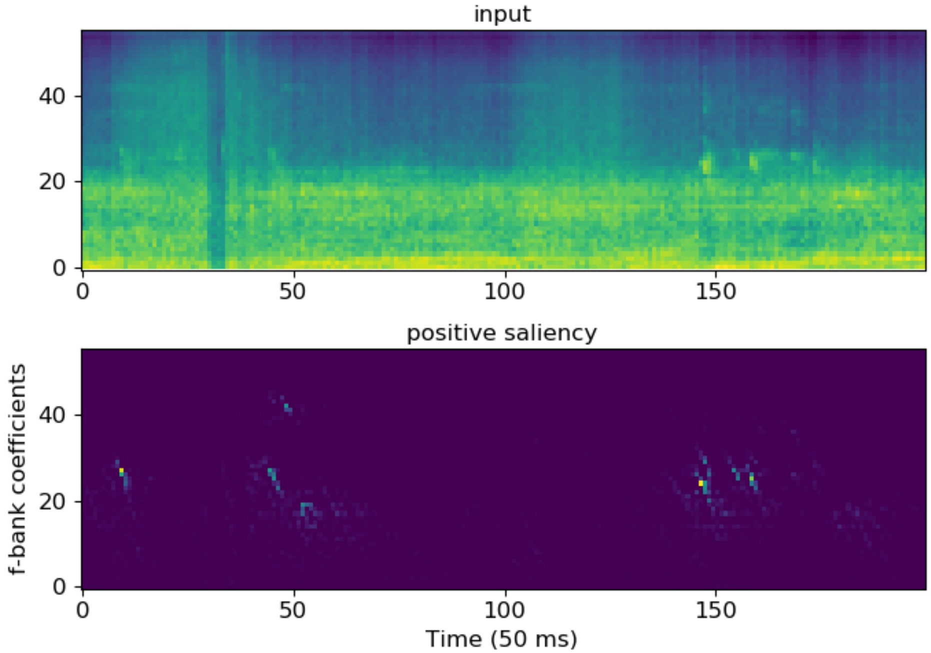
[B. Zhou et al, Learning Deep Features for Discriminative Localization. CVPR'16]

Deconvolution methods: handling the ReLu function



[Springenberg et al, ICLR 2015]

0070e5b1-110e-41f2-a9a5, P(bird): 0.966



Audio examples:

https://www.irit.fr/~Thomas.Pellegrini/

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