Apprentissage, réseaux de neurones et modèles graphiques (RCP209)
Deep Learning: open questions and perspectives

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Outline

CNN and invariance

CNN and invariance

- Standard ConvNets: limited invariance capacity (small shifts)
- ImageNet: single centered object ≠ other datasets (VOC, MS COCO)

⇒ **Learn shift invariance: region alignment !**

⇒ **Deep learning + structured prediction !**

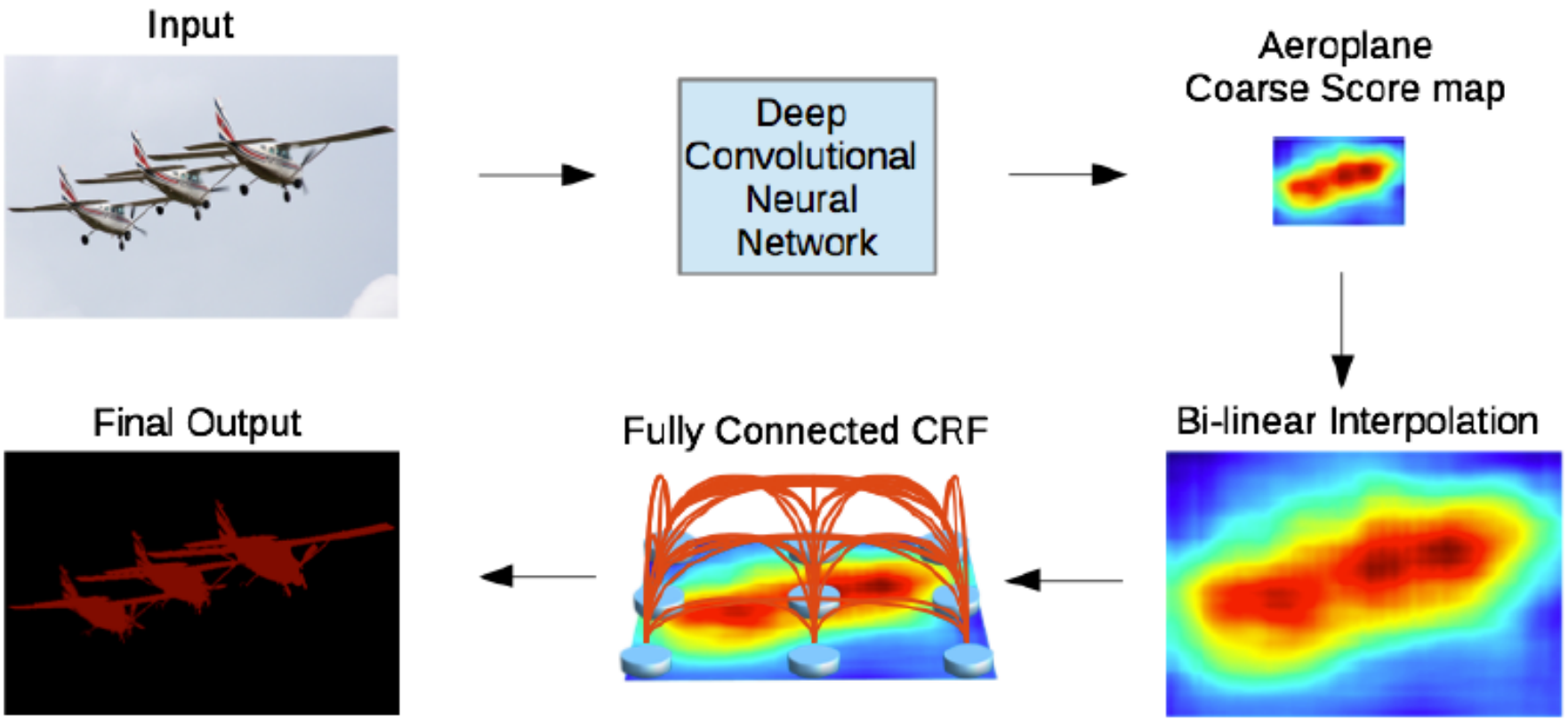
Deep Learning and Structured Prediction

- Structured prediction: graphical model in general (*e.g.* SSVM a specific model)
- Structured Prediction models (previous weeks): limited to log linear models with handcrafted features
- Combining Deep Learning & Structured Prediction
  - Solution: add a structured layer on top of your favorite deep model (*e.g.* ConvNet)
  - Issue : computational issue with Inference (and LAI for SSVM)
    - Methods for discrete outputs [CSYU15]
    - Recent models for continuous outputs [BM16, WFU16]
    - Approches to unroll inference: forward and backward passes of these deep structured models expressed as a set of standard layers [ZJRP$^+$15, BM16, WFU16]
      $\Rightarrow$ fast end-to-end training on GPUs.

Deep Learning and Structured Prediction

Ex: Semantic Segmentation

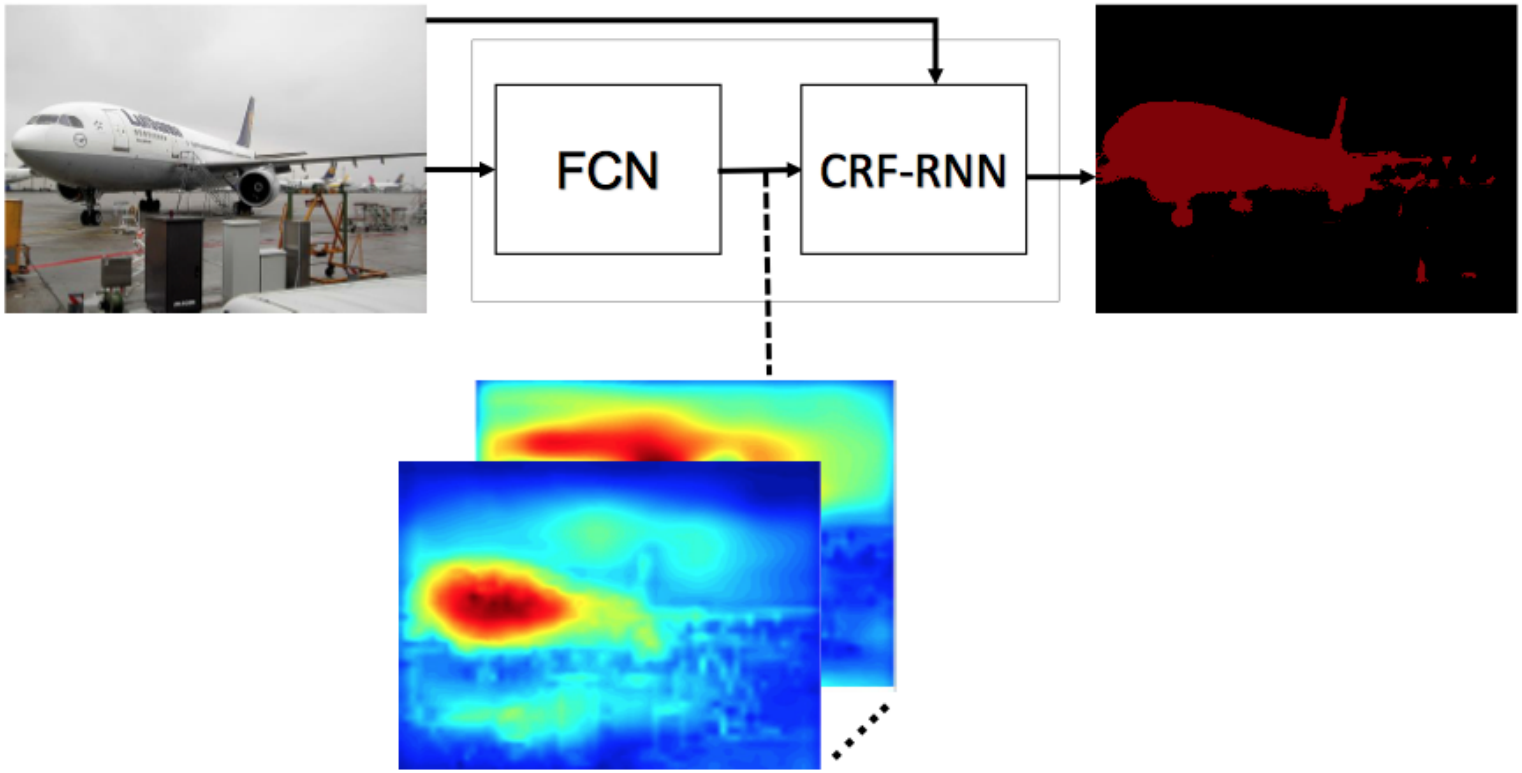
- Baseline model: DeepLab [CPK+15]: use Fully Convolutional Network (FCN) (fc layers cast as 1x1 conv + transfer layer)
- Per-pixel cross entropy loss
- CRF: post-processing to model correlation between outputs (pixel classes)



Deep Learning and Structured Prediction

Ex: Semantic Segmentation

- Extension: incorporate the CRF during training
  - Pair-wise term modeling correlation
  - End-to-end training with backprop
- CRF as RNN [ZJRP+15]: mean filed inference in CRF written as RNN



Recap: CNN and invariance

- Standard ConvNets: limited invariance capacity (small shifts)
- ImageNet: single centered object ≠ other datasets (VOC, MS COCO)

ImageNet

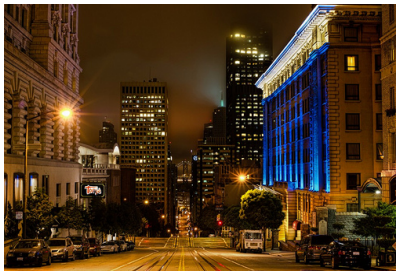



VOC 2007



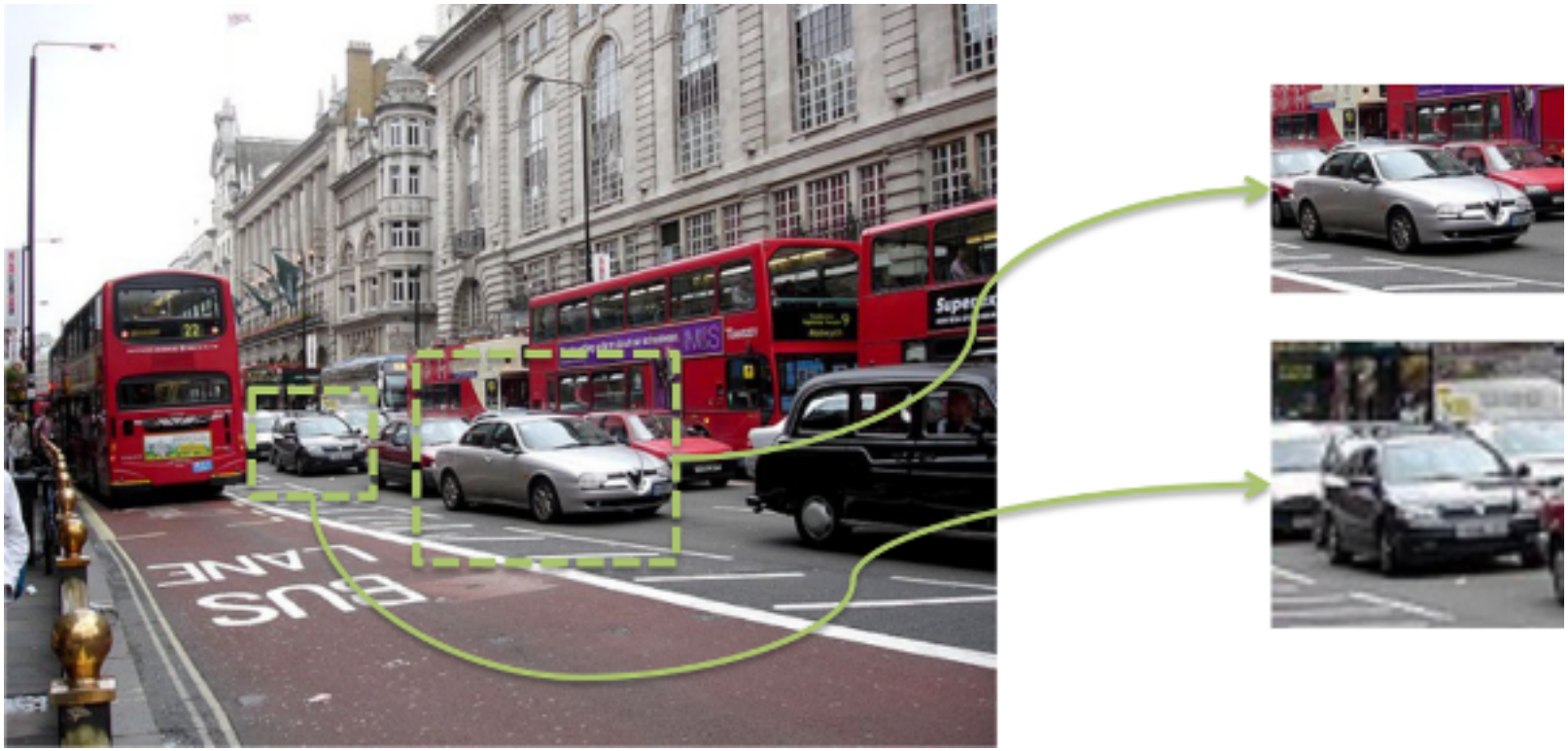

MS COCO






CNN and invariance

- Use regions to have images that look like ImageNet
- Using bounding box annotations [OBL+14]



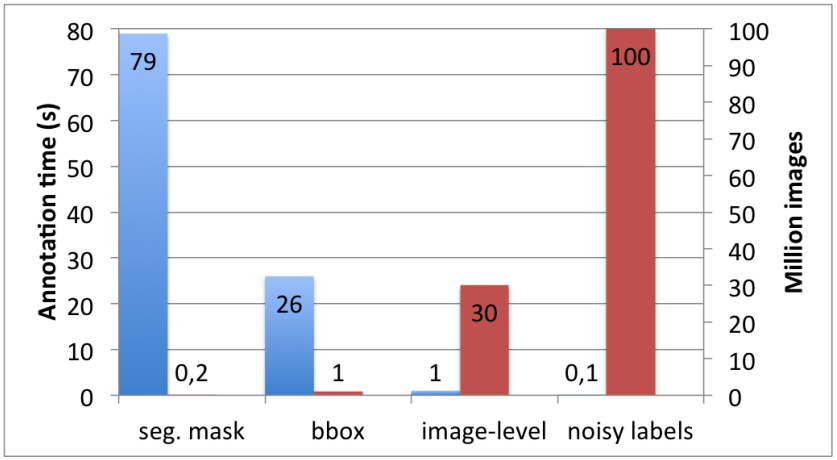
	Naive	Region
PASCAL VOC 2012	70.9%	78.7%

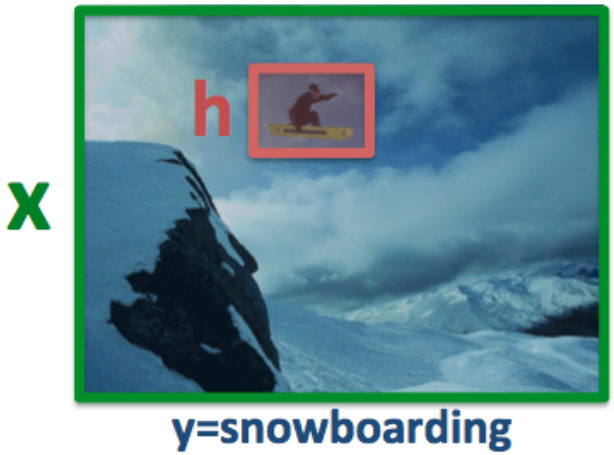
- Regions ⇒ better prediction

CNN and invariance

Weakly Supervised Learning

- Full annotations expensive ⇒ training with weak supervision [BRFFF16]



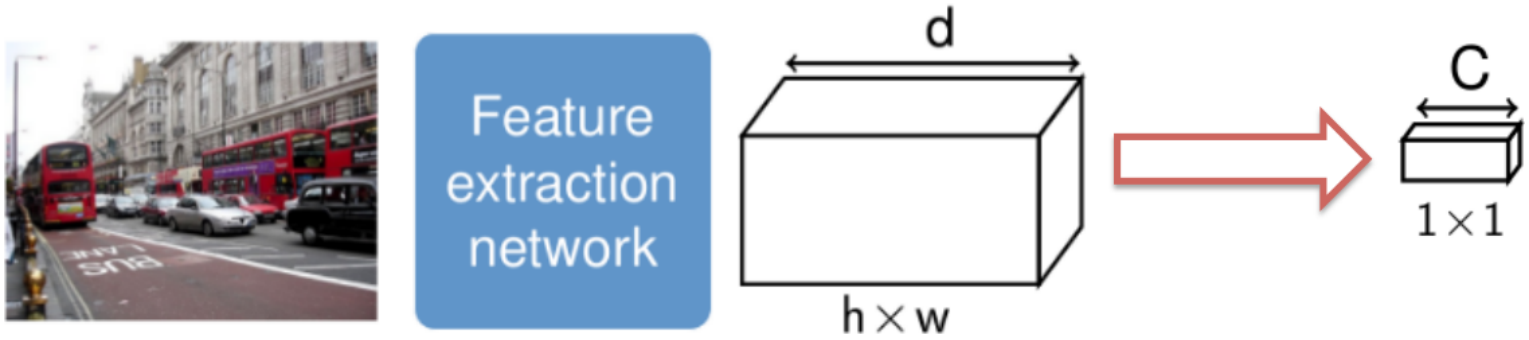


- **Incorporating latent variables h $\in \mathcal{H}$, *e.g.* training object detector from global image labels**

Variable	Notation	Space	Train	Test
Input	**x**	$\mathcal{X}$	observed	observed
Output	**y**	$\mathcal{Y}$	observed	unobserved
Latent	**h**	$\mathcal{H}$	unobserved	unobserved

Where to pool?

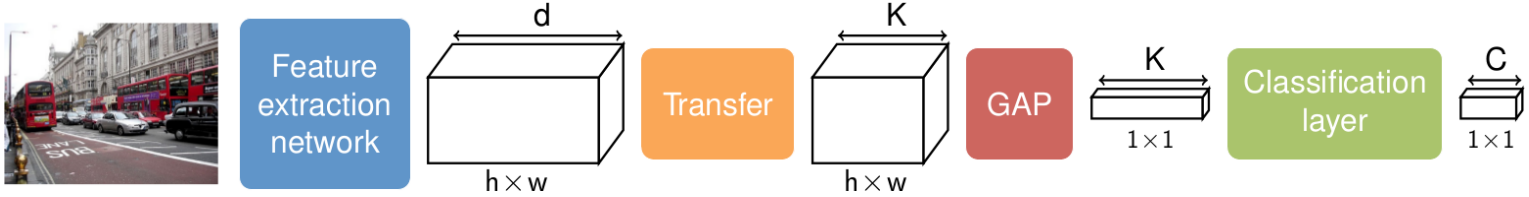
Transfer – Pooling – Classification



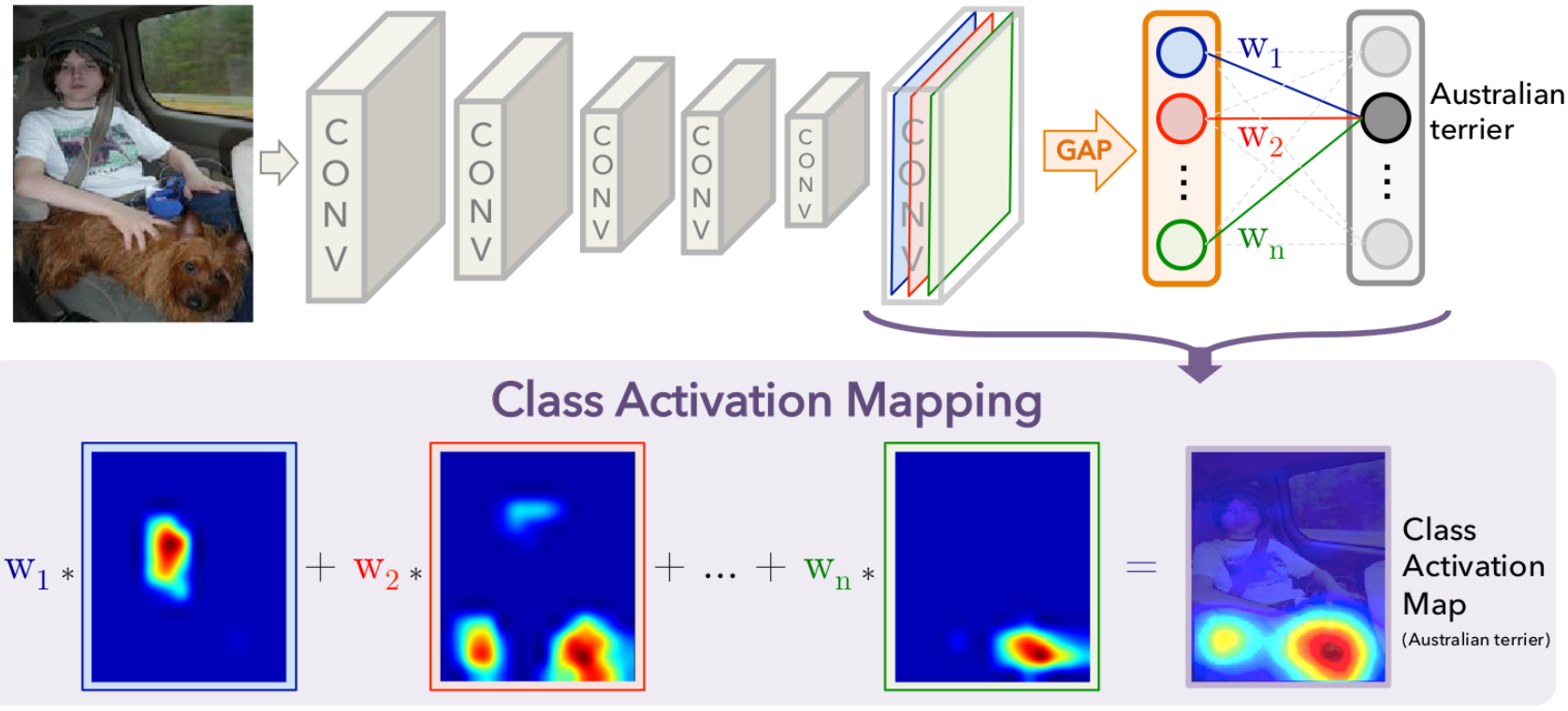
- Image-based strategy
- Region-based strategy

Image-based strategy

- Global Average Pooling [ZKA+16] (GoogLeNet, ResNet)

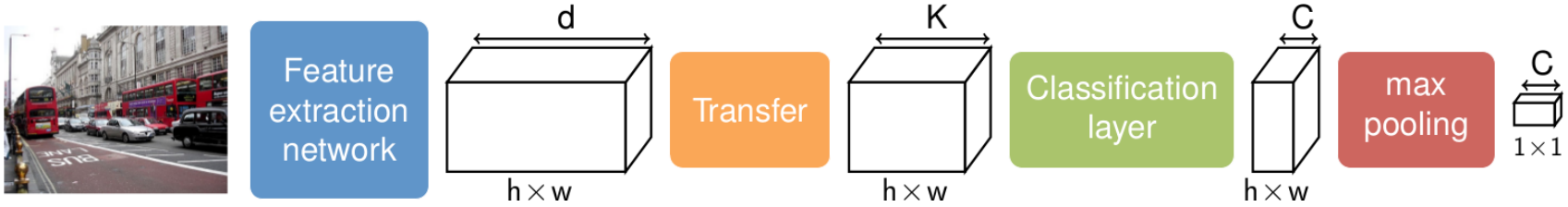


- Class Activation Mapping (CAM) for GAP

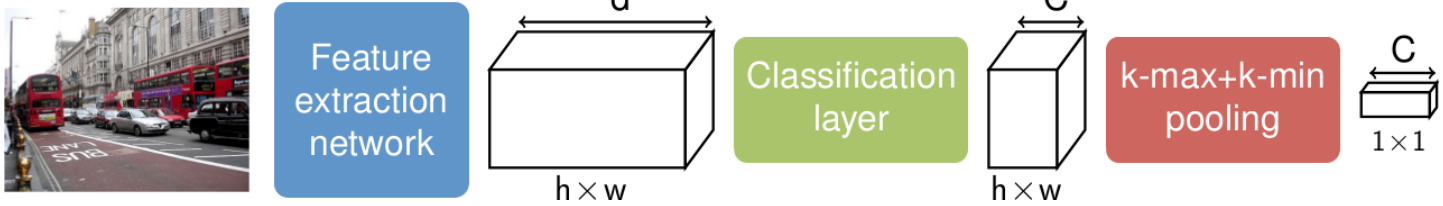


Region-based strategy

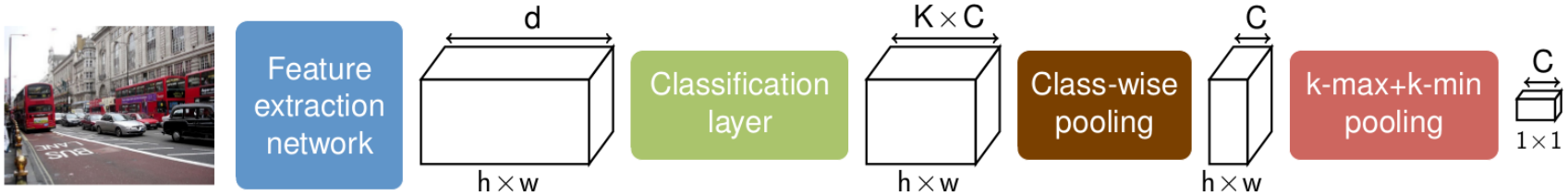
- Deep MIL [Oquab, CVPR15] [OBLS15]



- WELDON [Durand, CVPR16] [DTC16] (ProNet [Sun, CVPR16] [SPC+16])

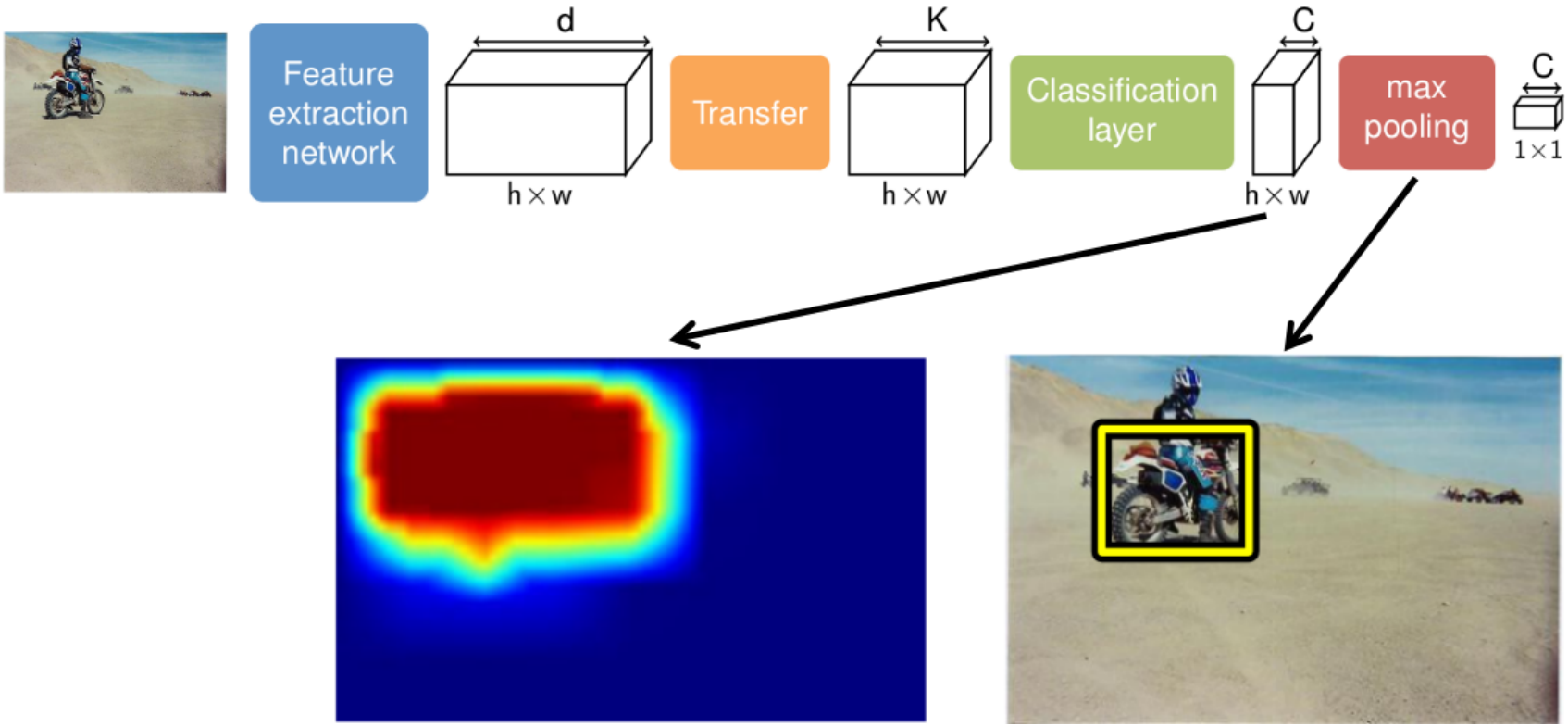


- WLIDCAT [Durand, CVPR17] [MDTC17]



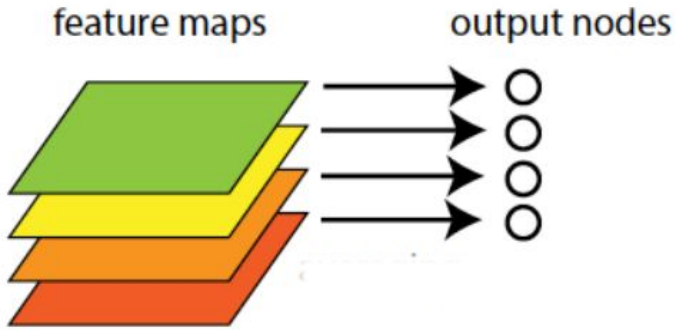
Region-based strategy

- CAM: direct in the map of depth C, *e.g.* for Deep MIL [OBLS15]



How to pool?

Pooling schemes



- Max [Oquab, CVPR15] [OBLS15]

$$y^c = \max_{i,j} z_{ij}^c \tag{1}$$

- GAP [Zhou, CVPR16] [ZKA+16]

$$y^c = \frac{1}{N} \sum_{i,j} z_{ij}^c \tag{2}$$

- LSE [Pinheiro, CVPR15] [PC15] / SPLeap [Kulkarni, ECCV16] [KJZ+16]

$$y^c = \frac{1}{\beta} \log \left(\frac{1}{N} \sum_{i,j} \exp(\beta \cdot z_{ij}^c) \right) \tag{3}$$

Max pooling limitation

- Classifying only with the max scoring region

- Loss of contextual information

Max pooling limitation

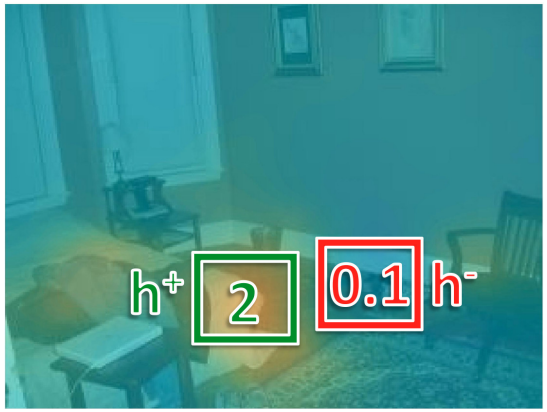
- Classifying only with the max scoring region

- Loss of contextual information

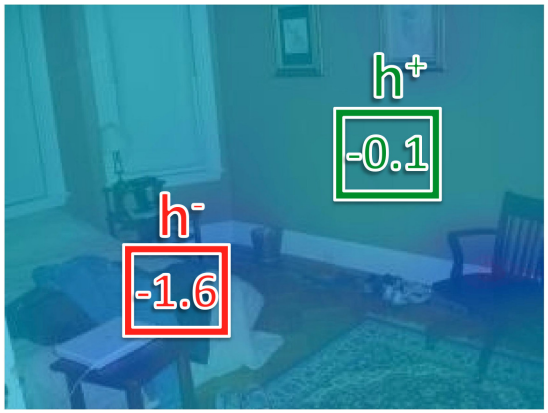
MANTRA [DTC15]: max+min pooling

- $\mathbf{h}^+$: presence of the class → high $\mathbf{h}^+$
- $\mathbf{h}^-$: localized evidence of the absence of class

original image



bedroom

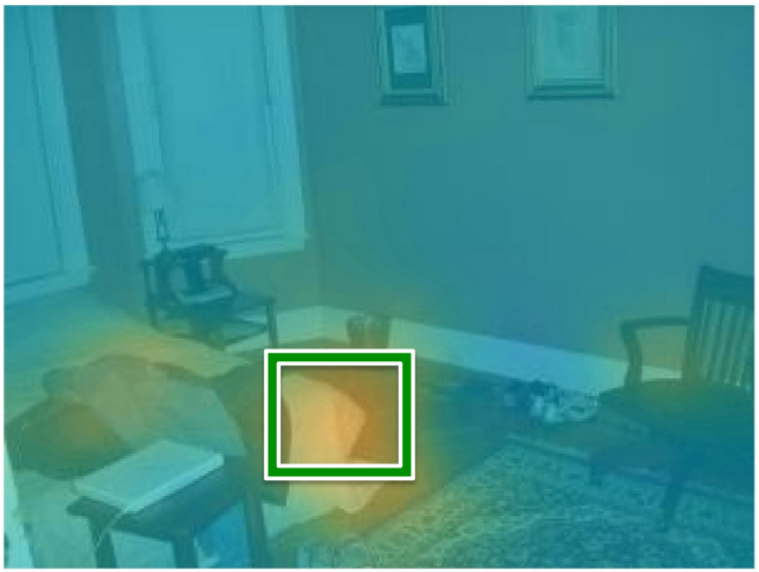


airport inside

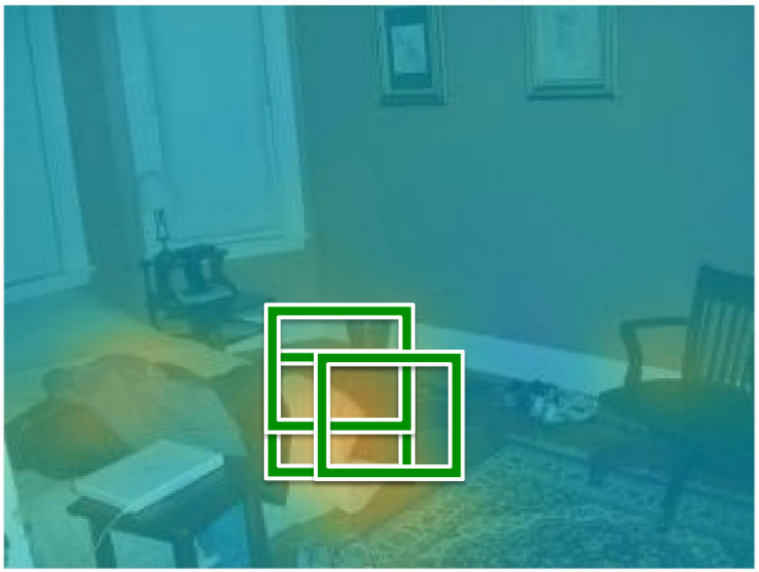
dining room

WELDON [DTC16] Pooling

- `max+min` strategy
- Top instances: using several regions, more robust region selection [Vasconcelos, CVPR15]



k=1



k=3

WELDON [DTC16] Pooling

- `max+min` strategy
- Top instances: using several regions, more robust region selection [Vasconcelos, CVPR15]

$$y^c = s^{top}_{k^+}(z^c) + s^{low}_{k^-}(z^c) \tag{4}$$

$$s^{top}_{k^+}(z^c) = \frac{1}{k^+} \sum_{i=1}^{k^+} i\text{-th-max}(z^c) \tag{5}$$

$$s^{low}_{k^-}(z^c) = \frac{1}{k^-} \sum_{i=1}^{k^-} i\text{-th-min}(z^c) \tag{6}$$

WILDCAT [MDTC17] Pooling

- `max+min`: complementary information
- Different kind of information

$$y^c = s^{top}_{k^+}(z^c) + \alpha \cdot s^{low}_{k^-}(z^c) \tag{7}$$

- α: trade off parameter.

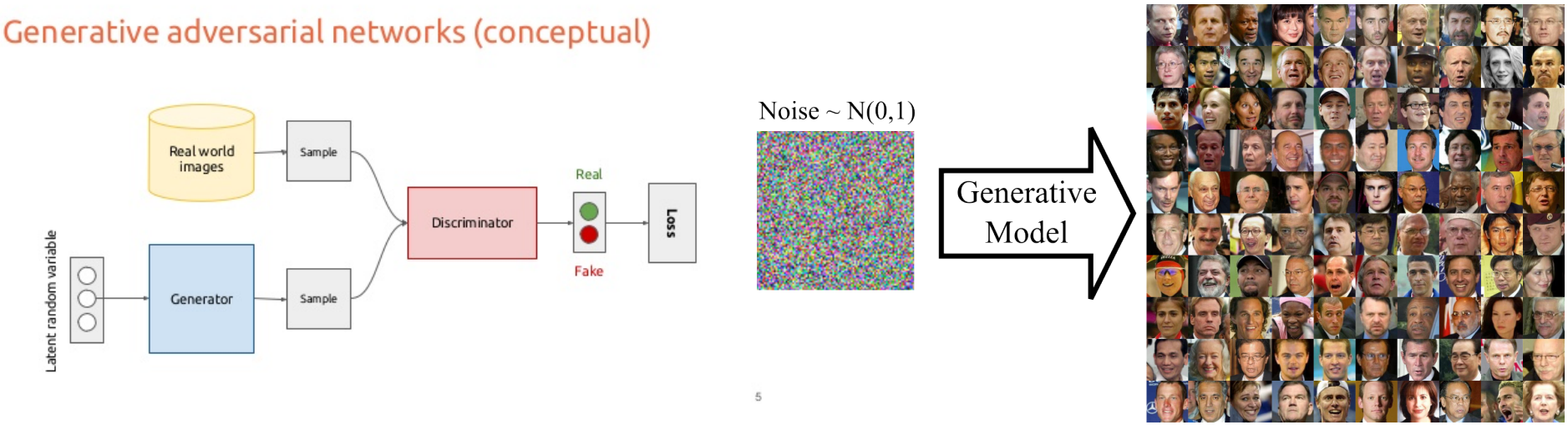
Pooling	k^+	k^-	α
Maximum	1	0	0
GAP	n	0	0
WELDON	k	k	1

Outline

Ongoing Issues in Deep Learning

Unsupervised Training

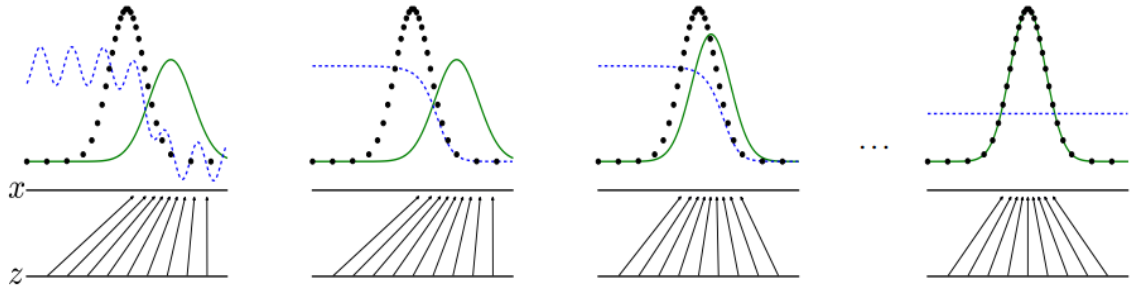
- Standard ways to perform unsupervised: learning representations fitting data well, *e.g.* Maximum likelihood, reconstruction error, *etc*
- Success of deep learning essentially for supervised problem
- Solution: cast unsupervised problem as a supervised one
  $\Rightarrow$ **auto-supervision**
  - Trendy example: Generative Adversarial Networks (GAN) [GPAM+14]



Ongoing Issues in Deep Learning

Unsupervised Training: GAN

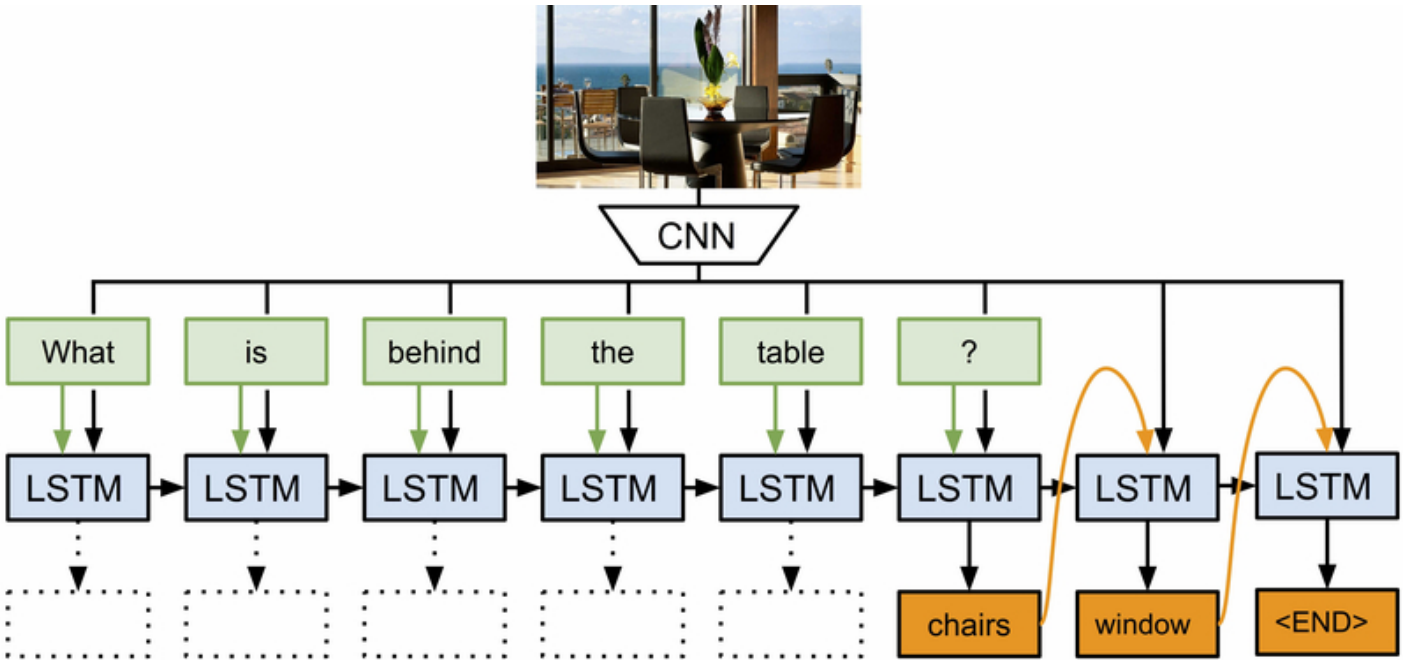
- Unsupervised problem ⇒ 2-player game theory problem
- Interesting results: optimal generator learns data distribution



Ongoing Issues in Deep Learning

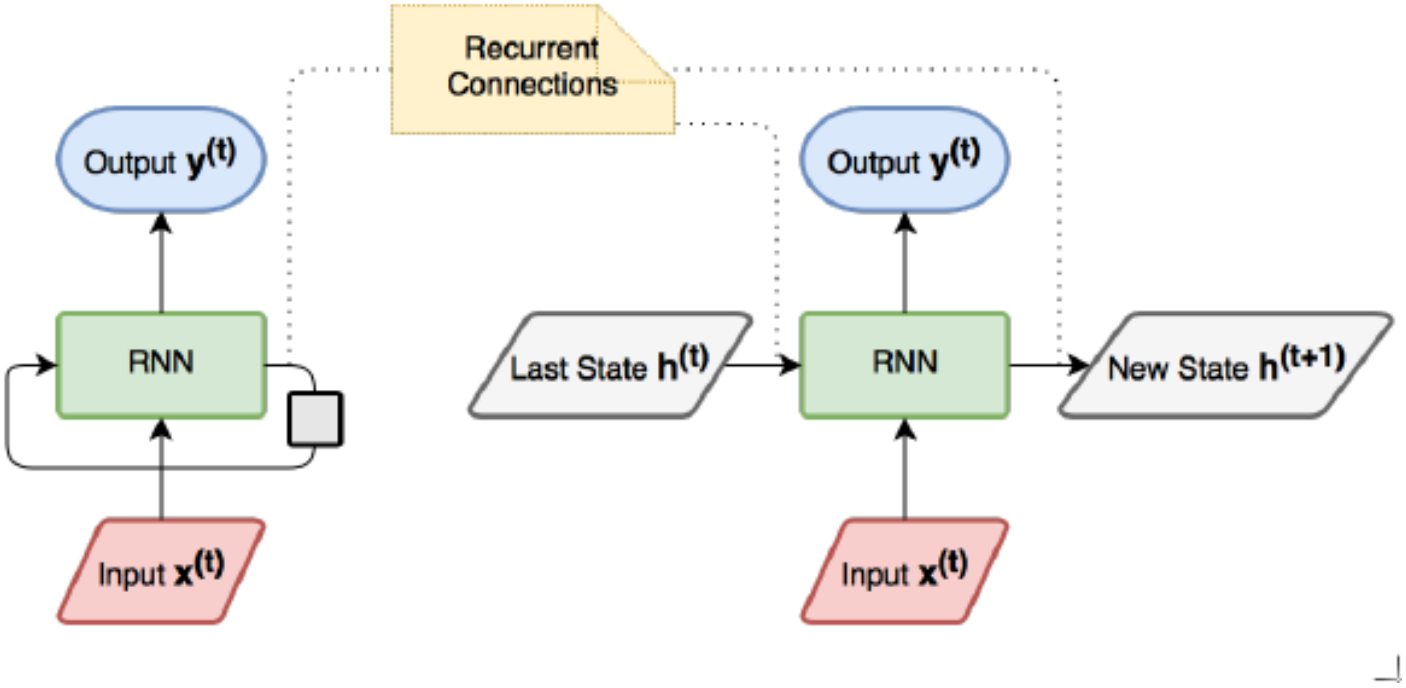
New Tasks in Artificial Intelligence

- Vision and language, Visual Question Answering (VQA), or image captioning
- Language: use of Reurrent Neural Networks (RNNs)



Credit: M. Malinowski [MRF15]

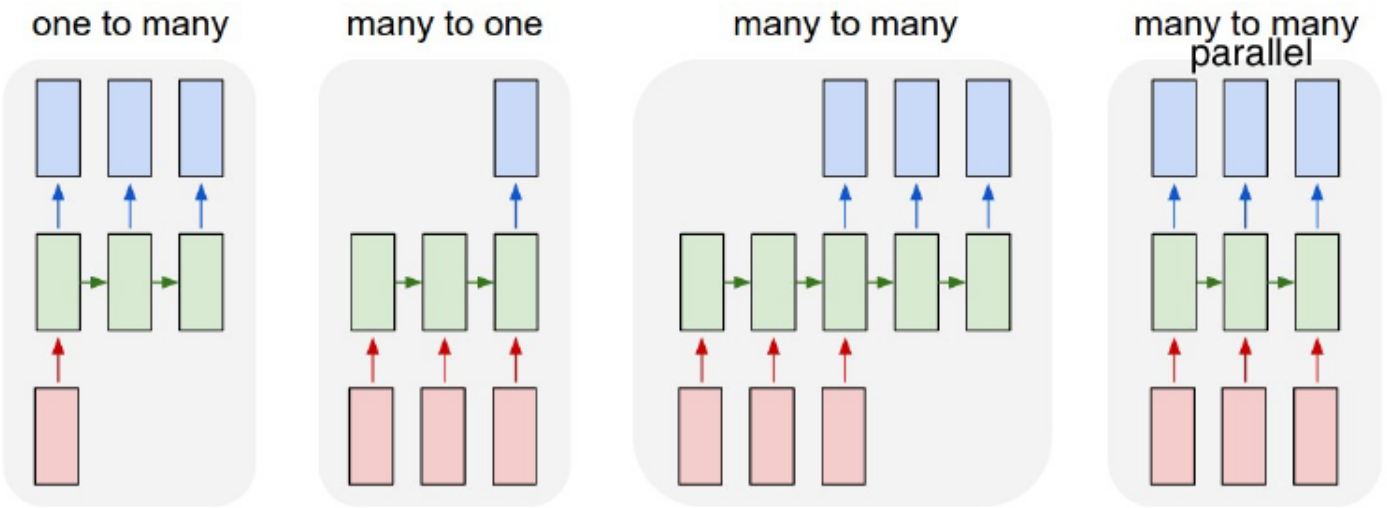
Reurrent Neural Networks (RNNs)



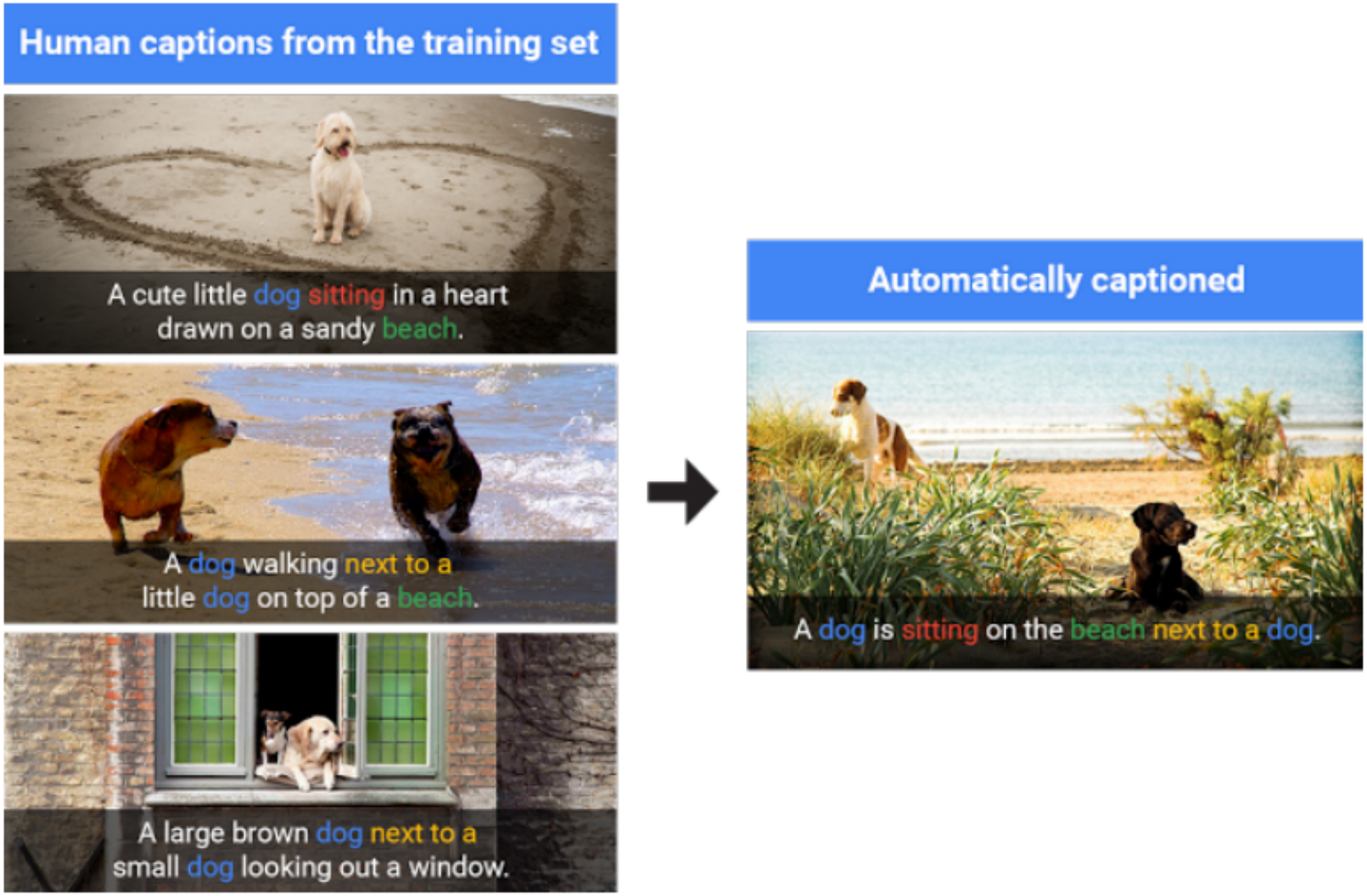
- Input vector $x(t)$, *e.g.* word (text) or image representation (CNN).
- Input/Output $h(t)$: vector representing model "short-term memory"
- Output vector $y(t)$: task dependent
- All parameters trained with backpropagation through time.

Reurrent Neural Networks (RNNs)

Sequence modeling with RNNs

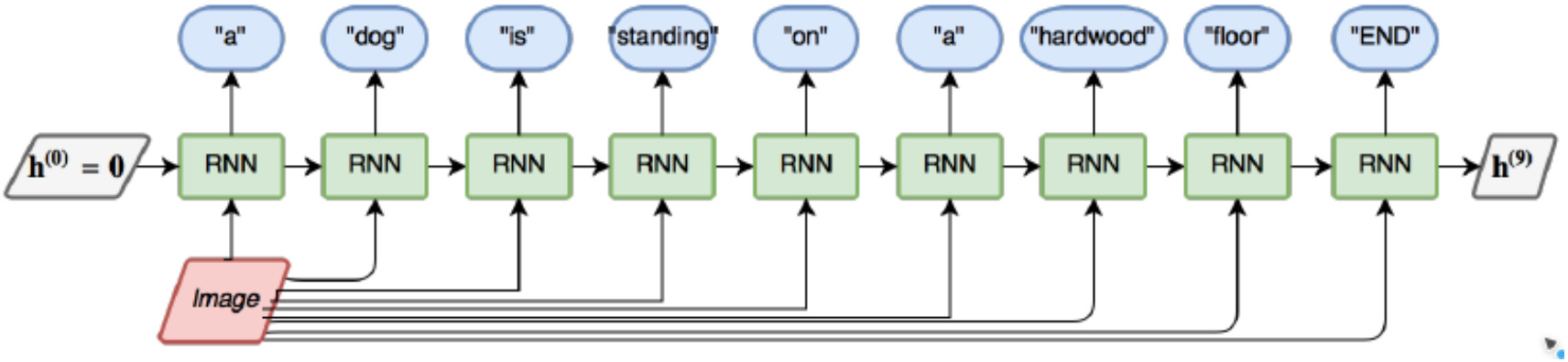


One to Many - Image captioning

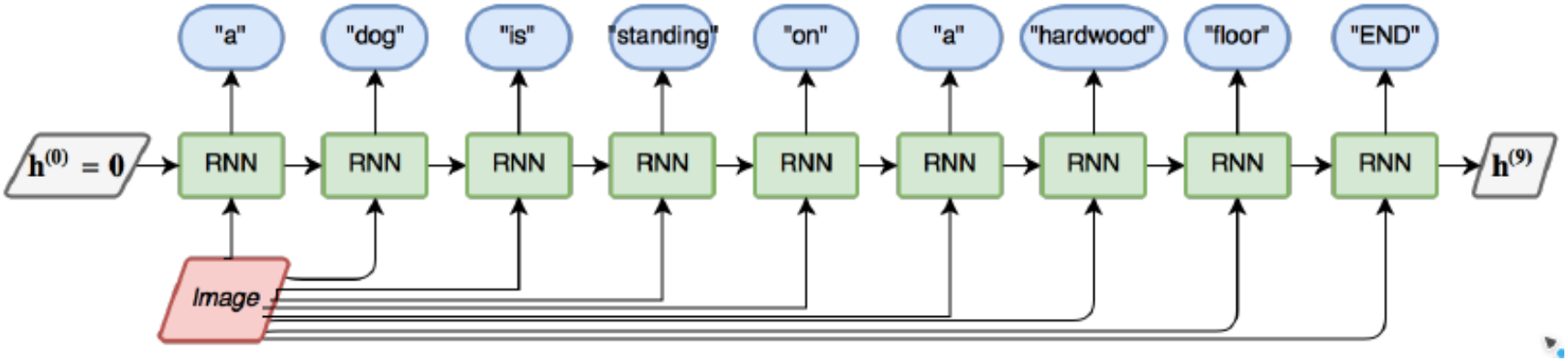


One to Many - Image captioning

- Show, Attend and Tell, Xu *et. al.*, ICML15 [XBK+15]



- Karpathy, CVPR15 [KL15]



Many to One - Visual Question Answering (VQA)

Goal : build a system that can answer questions about images

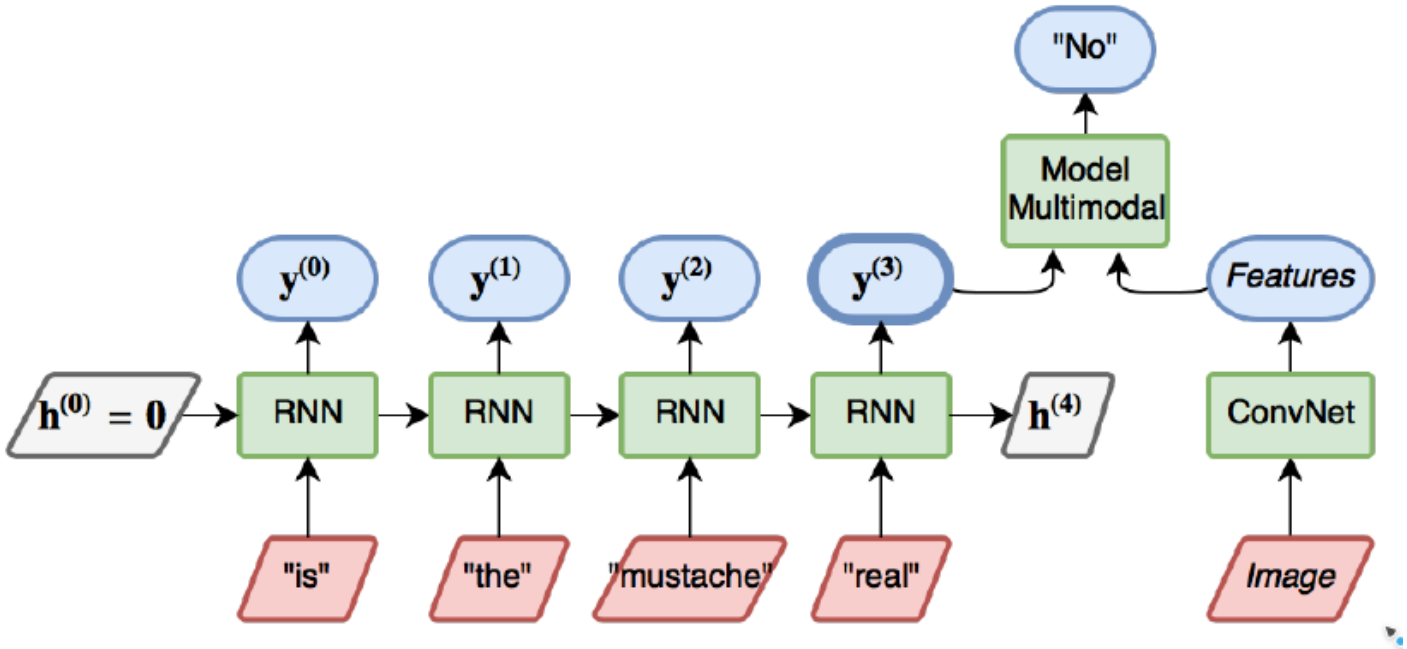
How many slices of pizza are there?
Is this a vegetarian pizza?

Does it appear to be rainy?
Does this person have 20/20 vision?

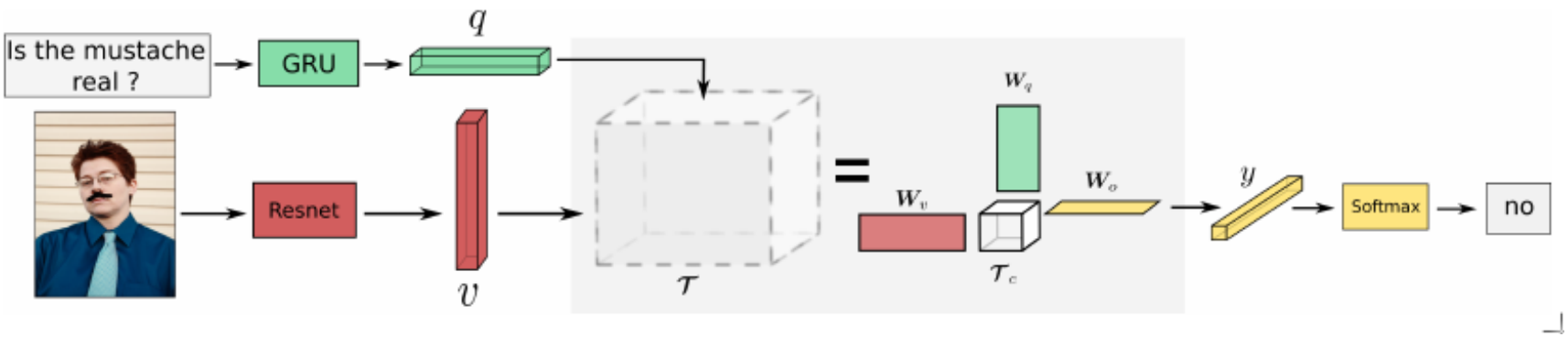
What color are her eyes?
What is the mustache made of?

Many to One - Visual Question Answering (VQA)

- Input: question & image
- Output: answer



VQA : Multi-modal Fusion

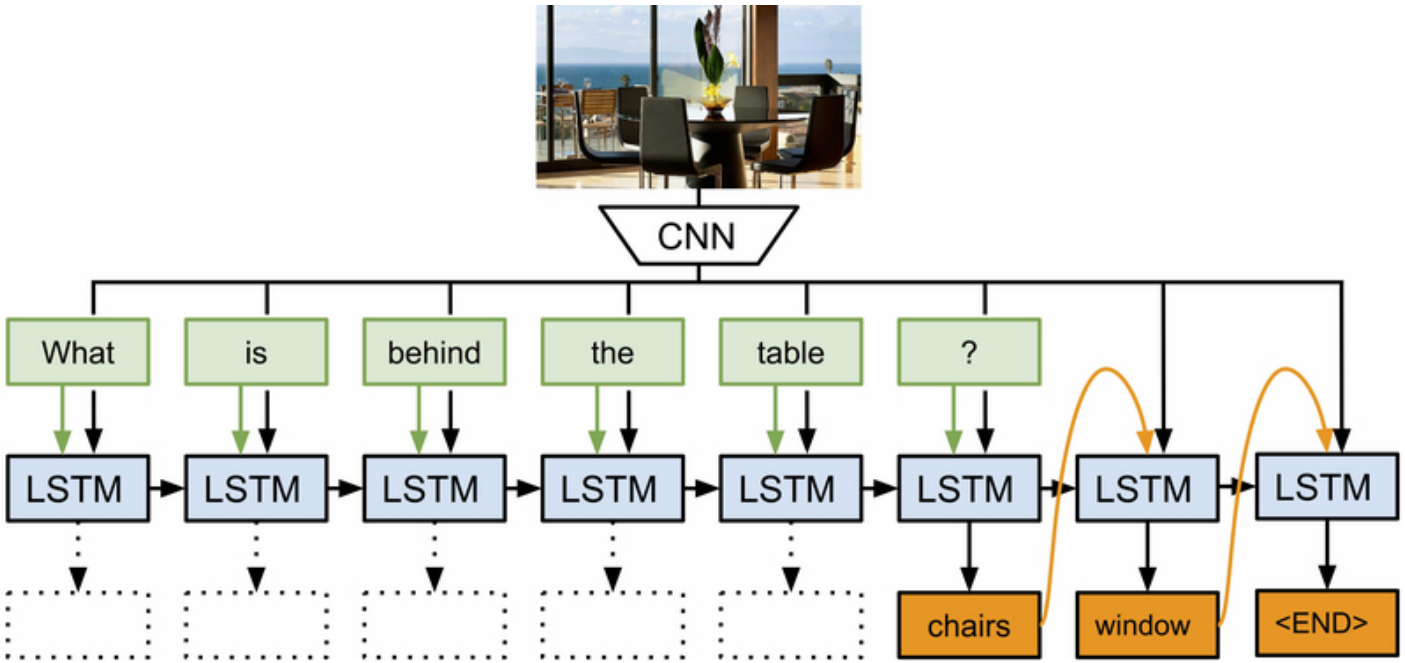


- Mono-modal representations:
  - Visual representation: ResNet-152
  - Question representation: pre-trained GRU
- How to perform multi-modal fusion ⇒ Tucker decomposition [BCCT17]

Ongoing Issues in Deep Learning

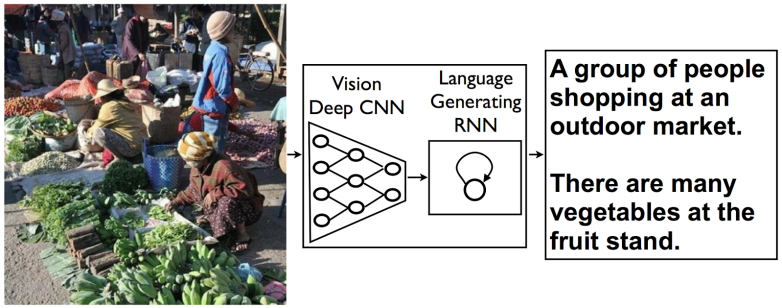
New Tasks in Artificial Intelligence

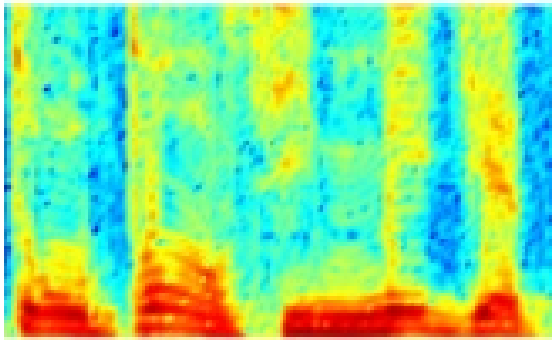
- But still a long way to go toward real AI ...



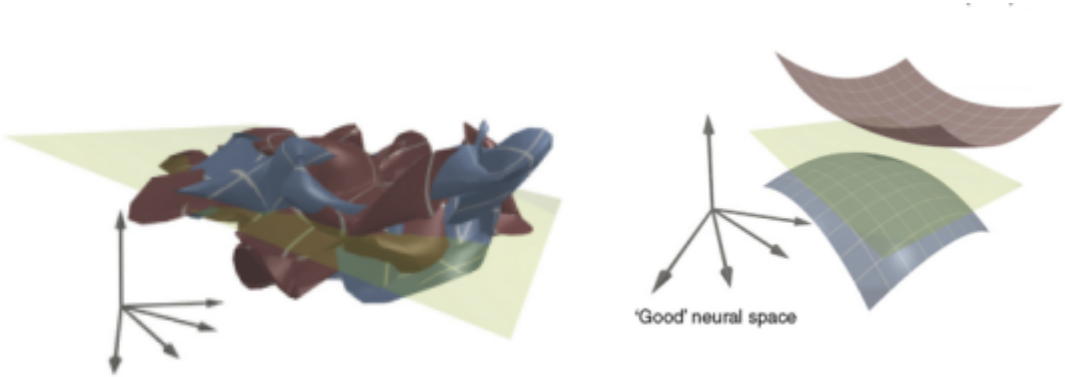
Credit: M. Malinowski [MRF15]

Conclusion





- Deep Learning: huge impact in terms of experimental results
- BUT: formal understanding still limited,
  - Optimization: non-convex problem
  - Model: ability to untangle manifold
  - Robustness to over-fitting & generalization

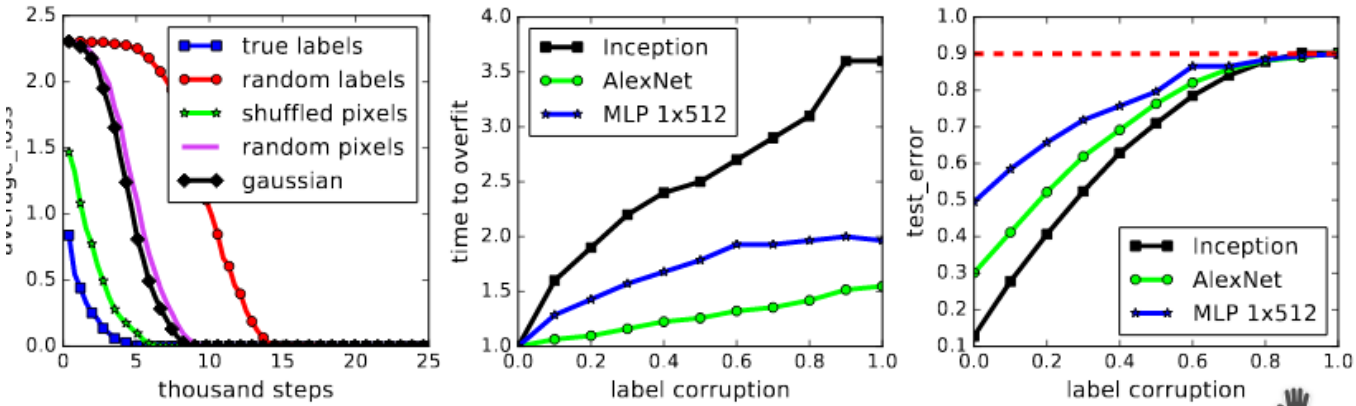


Deep Learning and generalization

- Rademacher complexity: capacity of a model to fit random label :

$$\mathcal{R}_n(\mathcal{H}) = E_\sigma \left[sup_{h \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^{n} \sigma_i h(x_i) \right]$$

- Rethinking generalization: Zhang *et. al.* ICLR17 [ZBH+17]



(a) learning curves (b) convergence slowdown (c) generalization error growth

  - Deep models easily fits random labels !!
  - $\mathcal{R}_n(\mathcal{H}) \approx 1 \Rightarrow$ no theoretical guarantee on generalization performances
- Classical learning theory insufficient to explain the good generalization behavior of deep models

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