

Self Supervision Techniques in CNNs

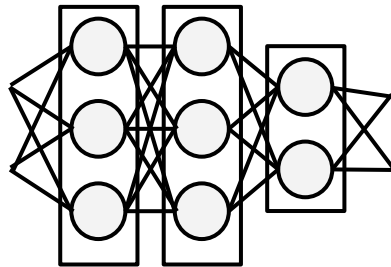
Varsha S
193079005



Outline

1. Motivation
2. Self supervision
3. Pretext Task
 - a. Inpainting
 - b. Jigsaw Puzzles

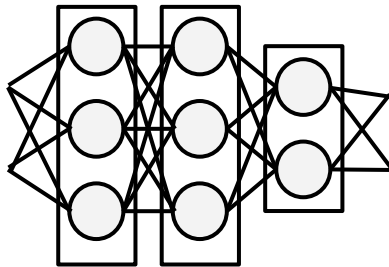
Motivation



Golden Retriever

Deep learning + ImageNet

Motivation



Golden Retriever

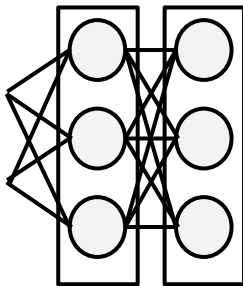
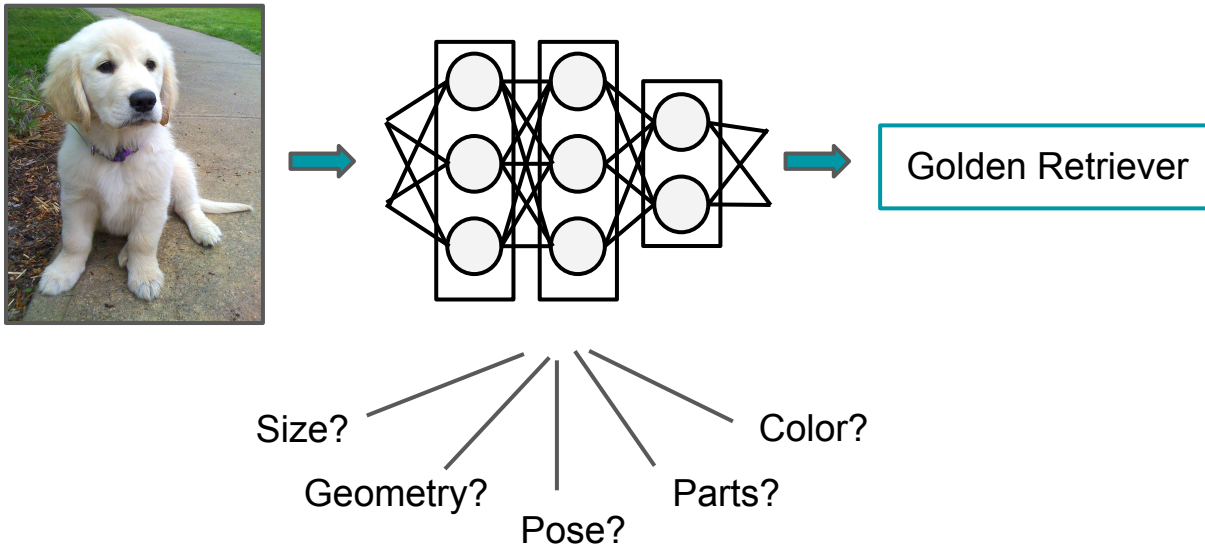
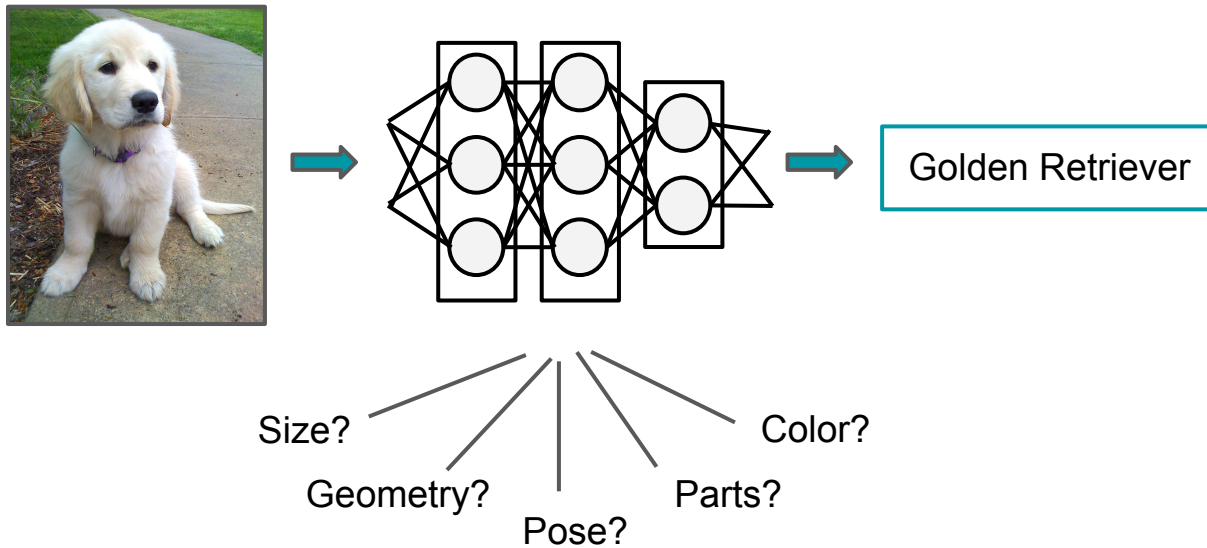


Image Segmentation
Detection
Depth Estimation
...

Motivation

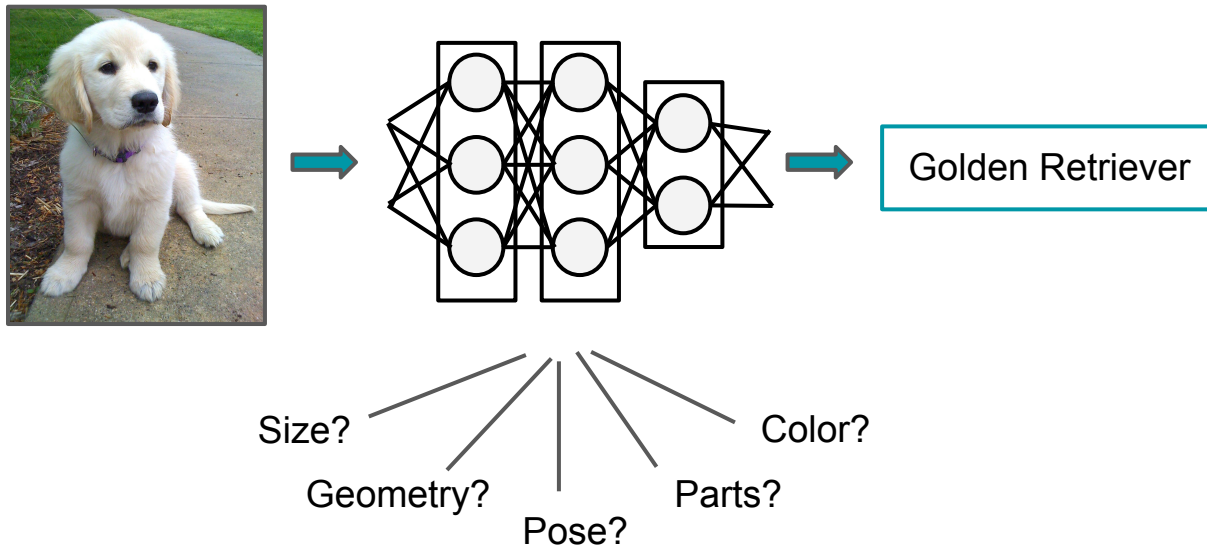


Motivation



Can the task be something else ?

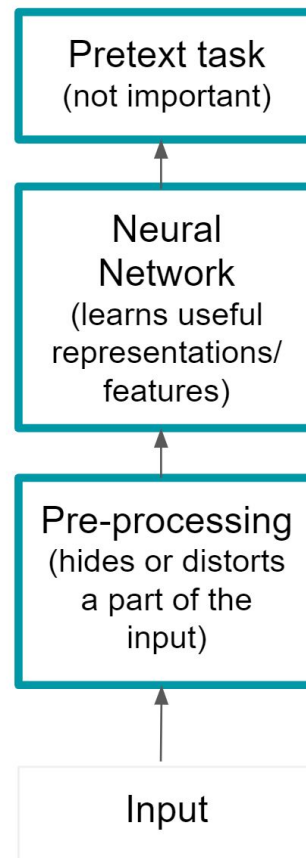
Motivation



Are the labels necessary?

Self Supervision

- Data provides supervision
- Goal - Learn good representations
- Task - Design pretext



PRETEXT TASK

A. INPAINTING

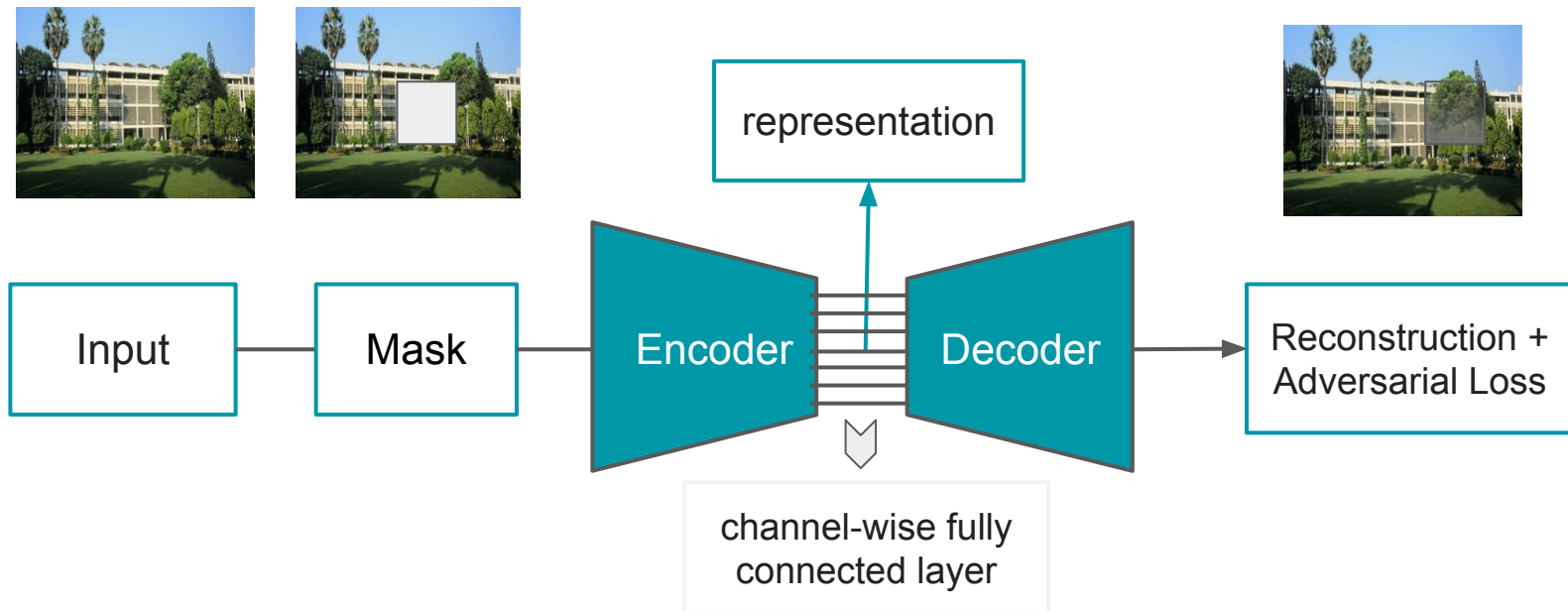
Inpainting - Context encoders



Inpainting - Context encoders



Inpainting - Context encoders



Inpainting - Loss function

- $\mathcal{L} = \lambda_{rec}\mathcal{L}_{rec} + \lambda_{adv}\mathcal{L}_{adv}$.
- $\mathcal{L}_{rec}(x) = \|\hat{M} \odot (x - F((1 - \hat{M}) \odot x))\|_2^2$,
- $\mathcal{L}_{adv} = \max_D \mathbb{E}_{x \in \mathcal{X}} [\log(D(x)) + \log(1 - D(F((1 - \hat{M}) \odot x)))]$



a) Masked Input



b) L2 Loss

c) L2 + adversarial
loss

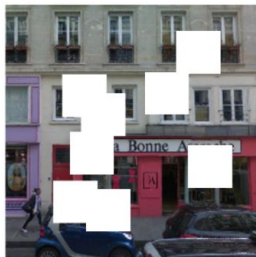
* where x is the ground truth image, F is the context encoder, M is a binary mask corresponding to the dropped image region with a value of 1 wherever a pixel was dropped and 0 for input pixels.

* Image source:- Deepak Pathak, et al, Context Encoders: Feature Learning by Inpainting. CVPR 2016

Inpainting - Masks



Center region

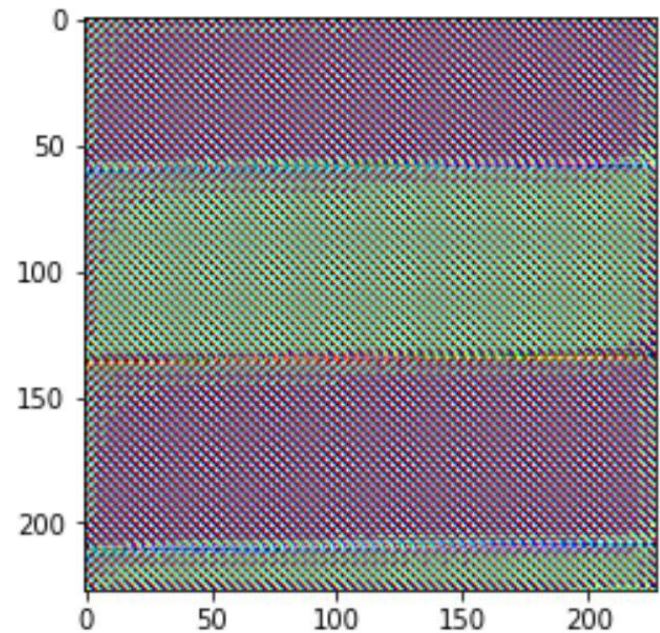
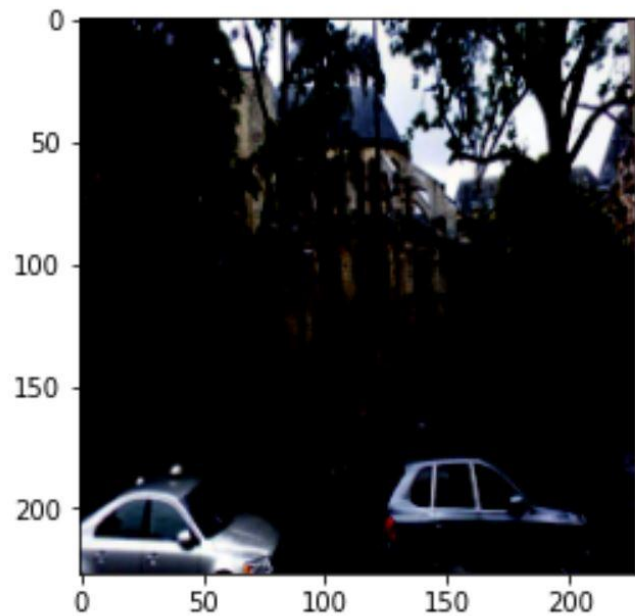


Random blocks



Random region

Inpainting - Results



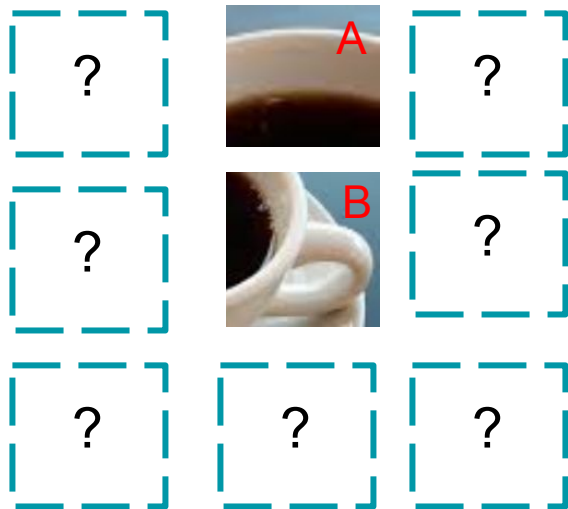
PRETEXT TASK

B. JIGSAW PUZZLES

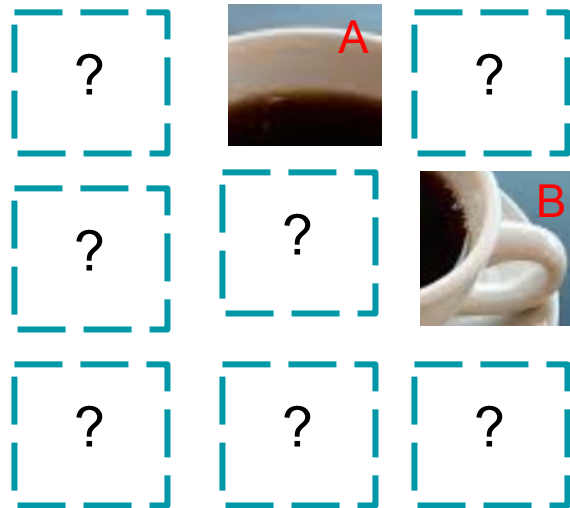
Inpainting



Inpainting

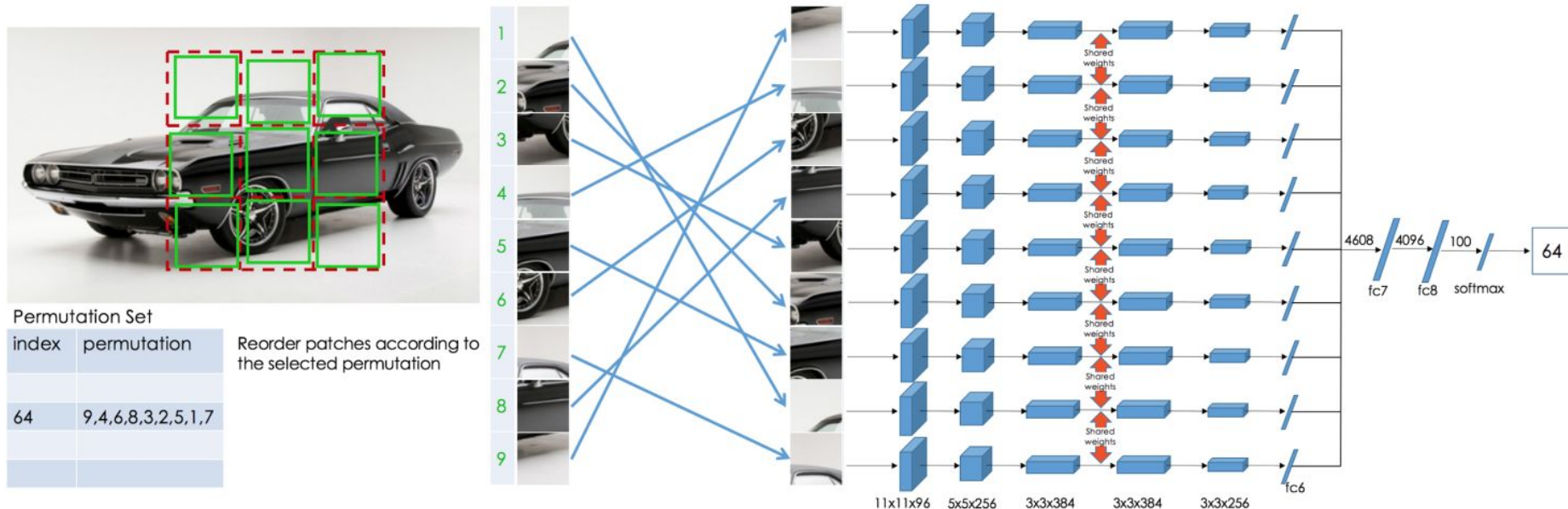


Inpainting

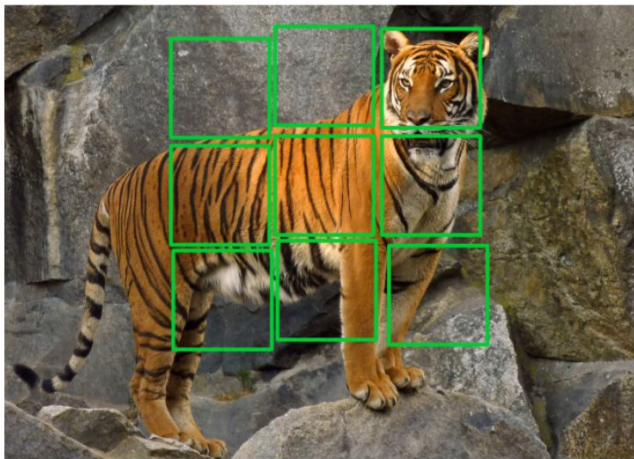


Jigsaw - Implementation

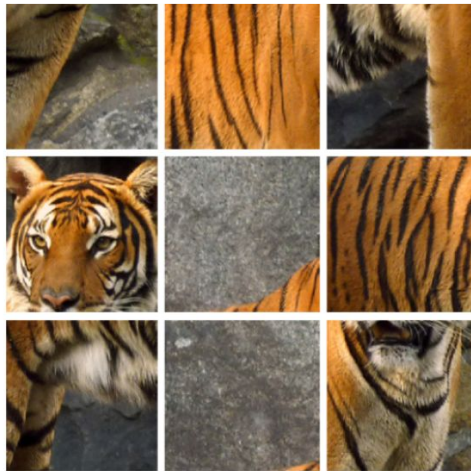
- Siamese network
- Permutations with large Hamming distance



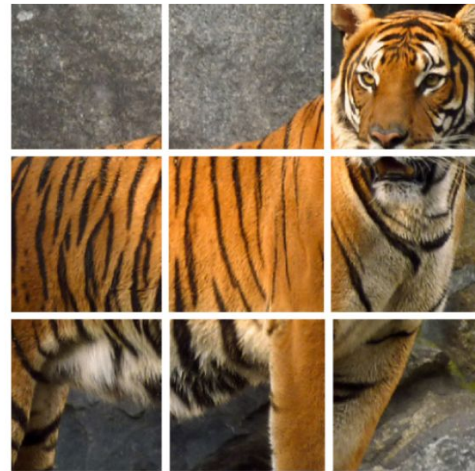
Jigsaw puzzle



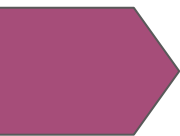
The image from which the tiles (marked with green lines) are extracted



Puzzle obtained by shuffling the tiles



Expected output



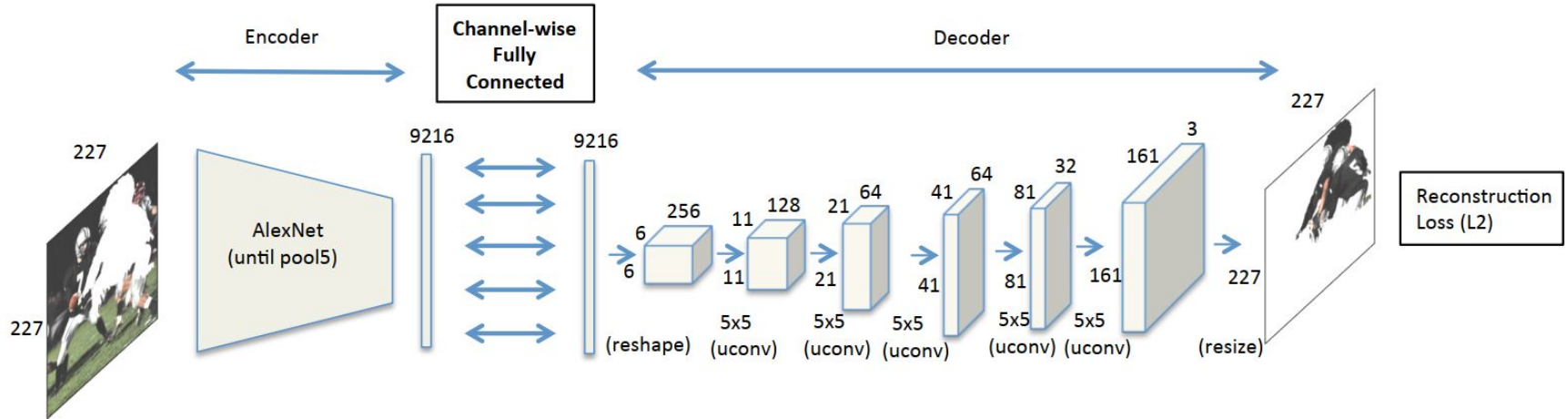
THANK YOU!



References

1. Deepak Pathak, Philipp Krahenbuhl, Jeff Donahue, Trevor Darrell and Alexei A. Efros, "Context Encoders: Feature Learning by Inpainting", CVPR 2016.
2. Noroozi, M. and P. Favaro. "Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles", ECCV (2016).
3. Carl Doersch, Abhinav Gupta, and Alexei A. Efros. "Unsupervised Visual Representation Learning by Context Prediction", ICCV 2015
4. Carl Doersch ICCV presentation - http://videolectures.net/iccv2015_doersch_visual_representation/

Inpainting - Architecture



Context encoder trained with reconstruction loss for feature learning by filling in *arbitrary region dropouts* in the input.

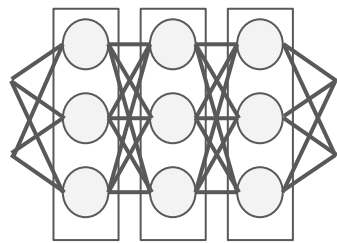
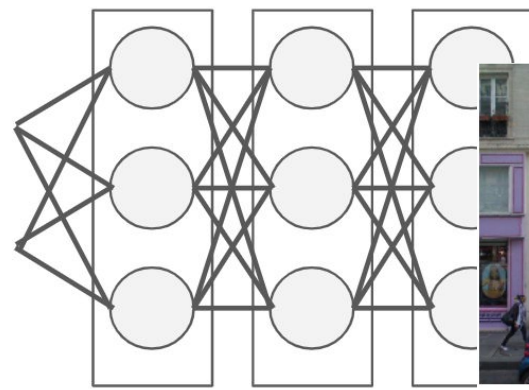


Motivation

- 1) In motivation add label intensive data is not available
- 2) Add how context helps in classification(beagle example from carl video)
- 3) How do these features get used later
- 4) Inpaintin
 - a) Encoder decoder diagram(shud make)
 - b)
 - c) maybe results(last slide)
- 5) Jigsaw
 - a) Siamese network(why it s needed n why it works)
 - b)
- 6)

- 2. Inpainting
- 3. Jigsaw
- 4. Outli

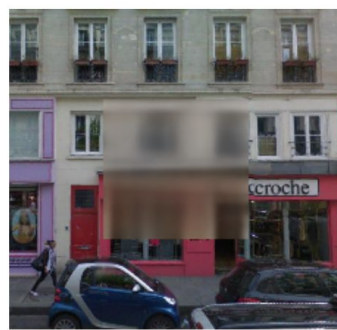
Outli



(a) Input context



(b) Human artist



(c) Context Encoder
(L2 loss)



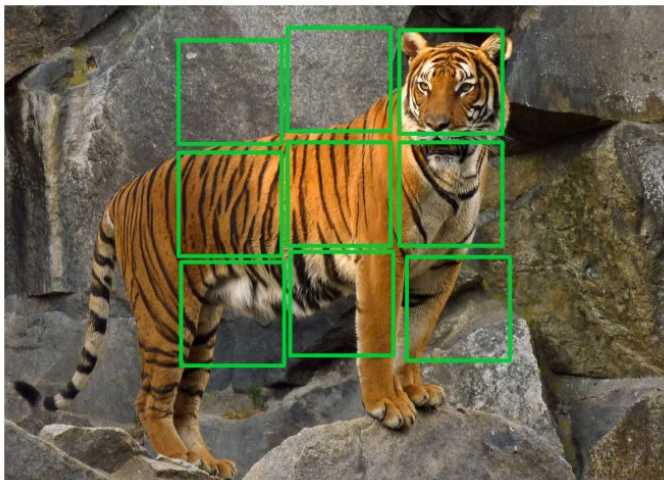
(d) Context Encoder
(L2 + Adversarial loss)

Pretext task
(not important)

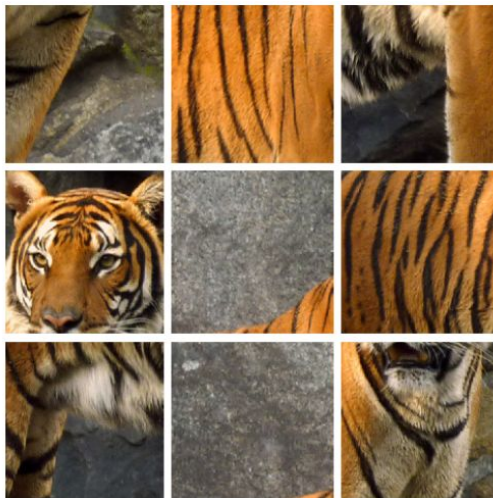
Neural
Network
(learns useful
presentations/
features)

Pre-processing
(adds or distorts
a part of the
input)

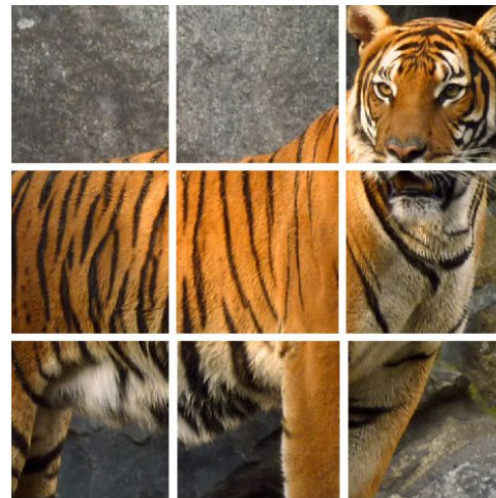
Input



The image from which the tiles (marked with green lines) are extracted



Puzzle obtained by shuffling the tiles



Expected output