DSME 6635: Artificial Intelligence for Business Research

Deep-Learning-Based Object Detection and Video Analysis

Renyu (Philip) Zhang

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Agenda

- Object Detection
- Video Analysis
- Video Analysis in Business/Econ Research

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Data Augmentation

- Reference: https://www.d2l.ai/chapter_computer-vision/image-augmentation.html
- Data Augmentation is used to create additional training data to make training more robust.
  - Data wrapping: transforming data in particular ways.
- The idea is to randomly transform/generate data while we are training:
  - Scale Variation
  - Rotation/mirror symmetry
  - Color Variation

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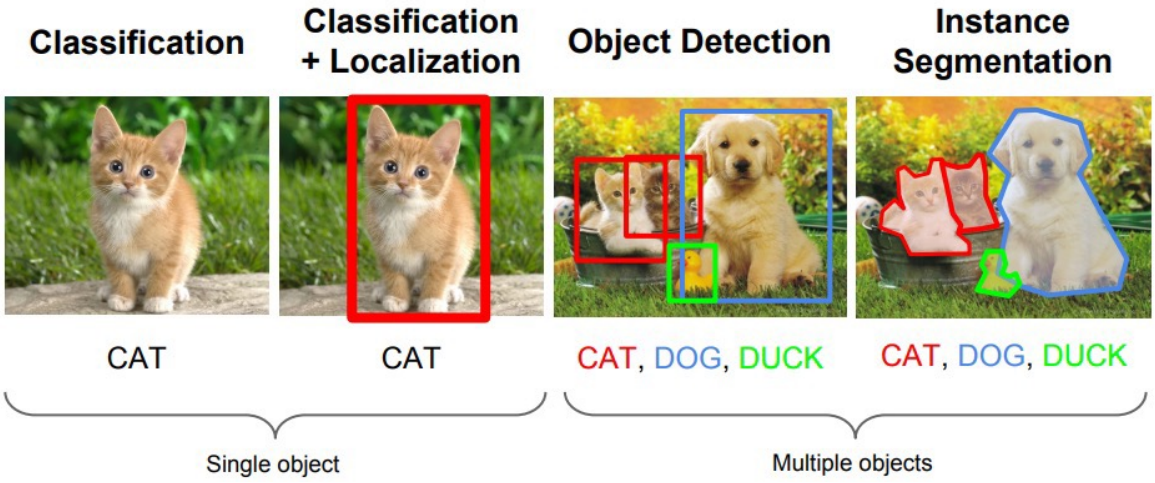
Beyond Image Classification

- So far, we focus on the task where we get one image and classify it into types of images.
- The next to do is object localization together with image classification.



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Classification + Localization

- Classification: C classes
  - Input: Image (x, y, z) matrix
  - Output: Class label c
  - Evaluation metric: Accuracy
- Localization:
  - Input: Image (x, y, z) matrix
  - Output: Box in the image (x, y, w, h)
  - Evaluation metric: Intersection area over the union area
- Object Detection: Classification + Localization

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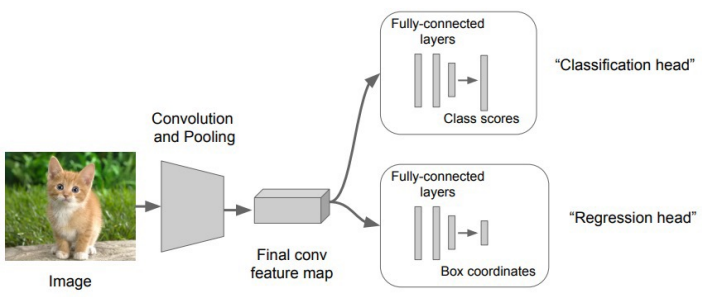
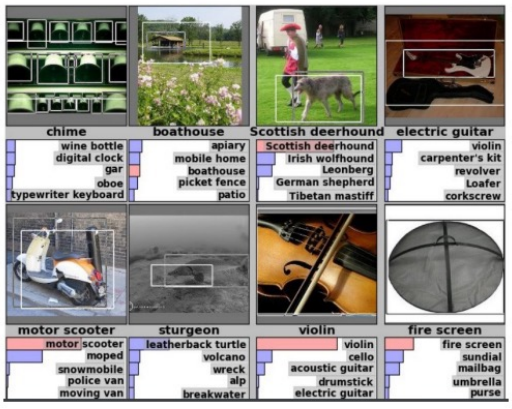
Classification + Localization

- Reference: http://cs231n.stanford.edu/slides/2023/lecture_11.pdf
- The simplest idea is to train a network that output both classes and coordinates (4 values, center of the box, width and height of the box).
- Train classification first, and then attach the regression head to only update the regression head parameters.





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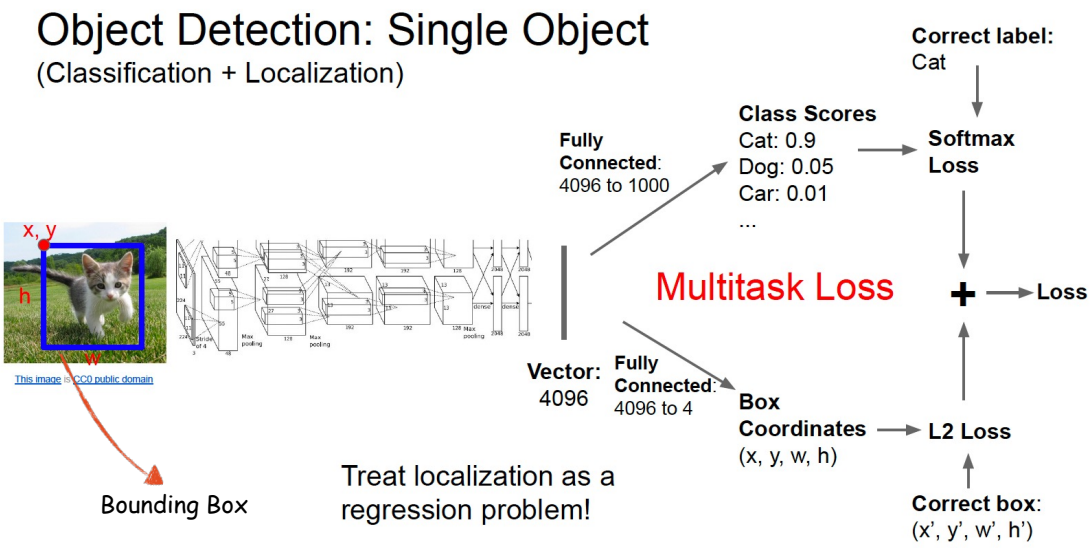
Single Object Detection

- Reference: http://cs231n.stanford.edu/slides/2023/lecture_11.pdf



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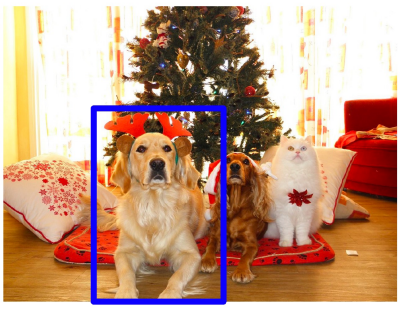
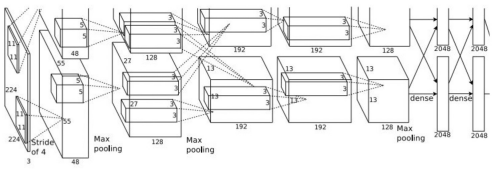
Multi-Object Detection

- Reference: http://cs231n.stanford.edu/slides/2023/lecture_11.pdf

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background





Dog? YES
Cat? NO
Background? NO

8

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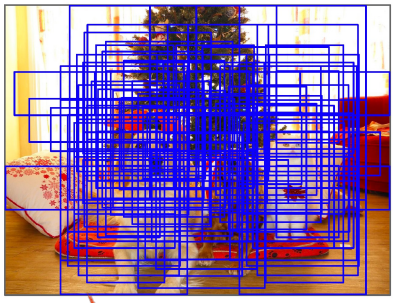
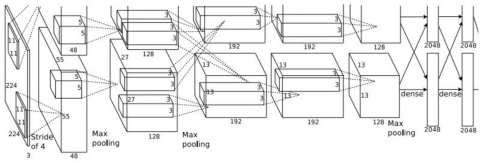
Multi-Object Detection

- Reference: http://cs231n.stanford.edu/slides/2023/lecture_11.pdf

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background





Dog? NO
Cat? YES
Background? NO

Problem: Need to apply CNN to huge number of locations, scales, and aspect ratios, very computationally expensive!

A lot of sliding windows.

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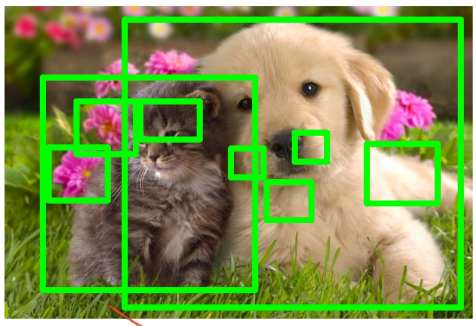
Region Proposals: Selective Search

- Reference: http://cs231n.stanford.edu/slides/2023/lecture_11.pdf
- Selective Search starts by over-segmenting the image into a lot of initial regions and then merges these regions based on various similarity criteria such as color, texture, size, and shape compatibility. The process results in a set of region proposals that potentially contain objects.

Selective Search



Region Proposals

Alexe et al, "Measuring the objectness of image windows", TPAMI 2012
Uijlings et al, "Selective Search for Object Recognition", IJCV 2013
Cheng et al, "BING: Binarized normed gradients for objectness estimation at 300fps", CVPR 2014
Zitnick and Dollar, "Edge boxes: Locating object proposals from edges", ECCV 2014

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Region-Based CNN (R-CNN)

Rich feature hierarchies for **accurate object detection** and **semantic segmentation**
R Girshick, J Donahue, T Darrell… - … and pattern **recognition**, 2014 - openaccess.thecvf.com
… **Object detection** with R-CNN Our **object detection** system consists of three modules. The first generates category-independent region proposals. These proposals define the set of …
☆ Save 99 Cite Cited by 35902 Related articles All 46 versions »

http://cs231n.stanford.edu/slides/2023/lecture_11.pdf
https://www.d2l.ai/chapter_computer-vision/rcnn.html

One CNN trained for each RoI.

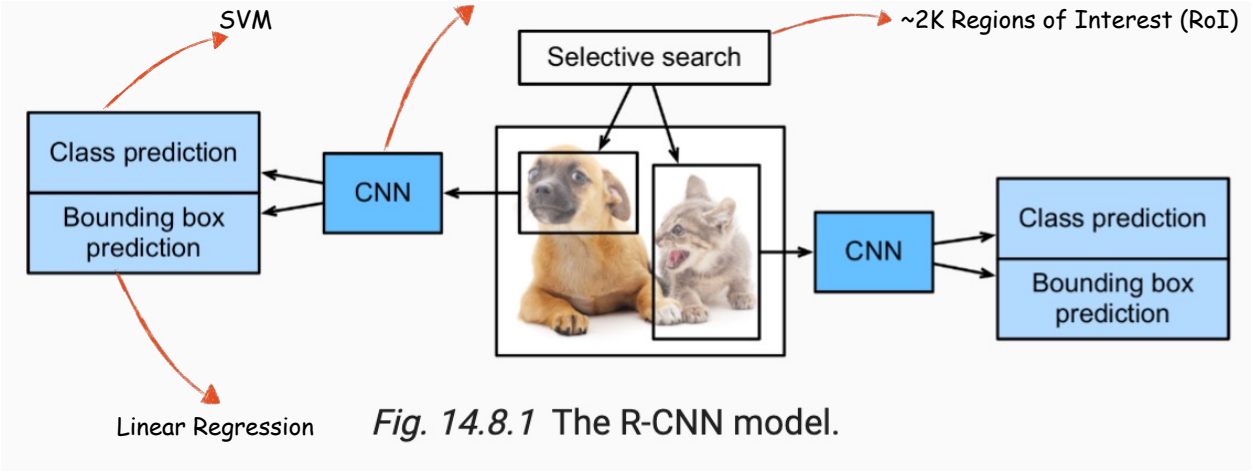

Fig. 14.8.1 The R-CNN model.

R-CNN is computationally very expensive, even with pre-trained CNNs.

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Fast R-CNN

Fast r-cnn
R Girshick - … of the IEEE international conference on …, 2015 - openaccess.thecvf.com
This paper proposes a **Fast** Region-based Convolutional Network method (**Fast R-CNN**) for object detection. **Fast R-CNN** builds on previous work to efficiently classify object proposals …
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http://cs231n.stanford.edu/slides/2023/lecture_11.pdf
https://www.d2l.ai/chapter_computer-vision/rcnn.html

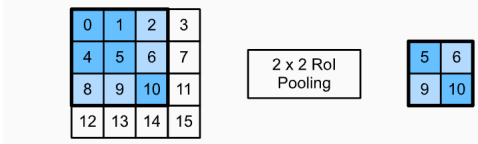
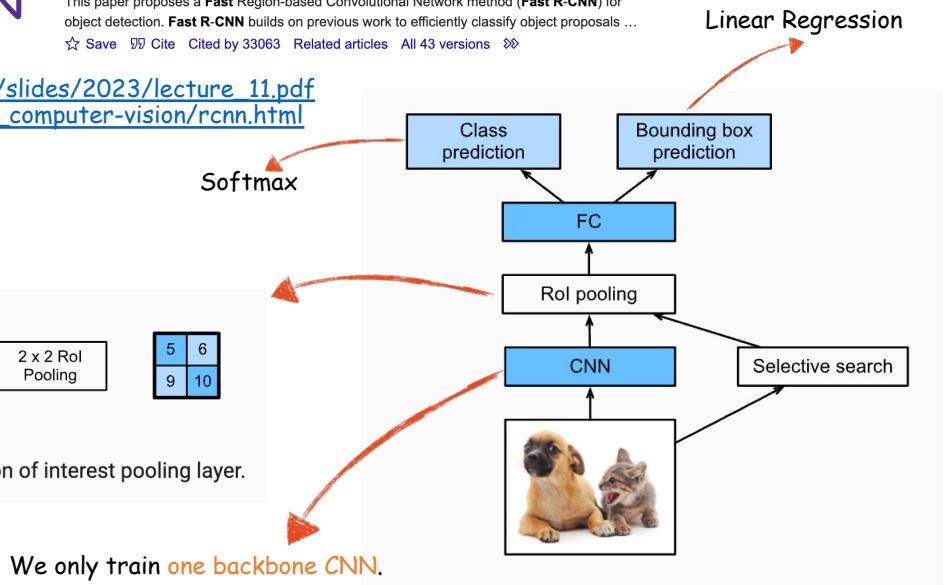


Fig. 14.8.3 A 2×2 region of interest pooling layer.



We only train one backbone CNN.

Fig. 14.8.2 The fast R-CNN model.

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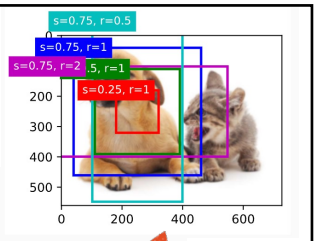
Faster R-CNN

http://cs231n.stanford.edu/slides/2023/lecture_11.pdf
https://www.d2l.ai/chapter_computer-vision/rcnn.html



Background or Objects

Class prediction | Bounding box prediction | FC | Binary class prediction | Bounding box prediction | RoI pooling | NMS | Anchor box | CNN | Conv

Region proposal network

Non-Maximum Suppression: Keeps only the most probable bounding box and removing the less probable, overlapping ones.

[PDF] **Faster r-cnn**: Towards real-time object detection with **region** proposal networks
S Ren, K He, R Girshick, J Sun - Advances in neural ..., 2015 - proceedings.neurips.cc
... For this purpose, we train a **Fast R-CNN model** by using the 2k SS proposals and ZF net. We fix this detector and evaluate the detection mAP by changing the proposal regions used at ...
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Fig. 14.8.4 The faster R-CNN model.

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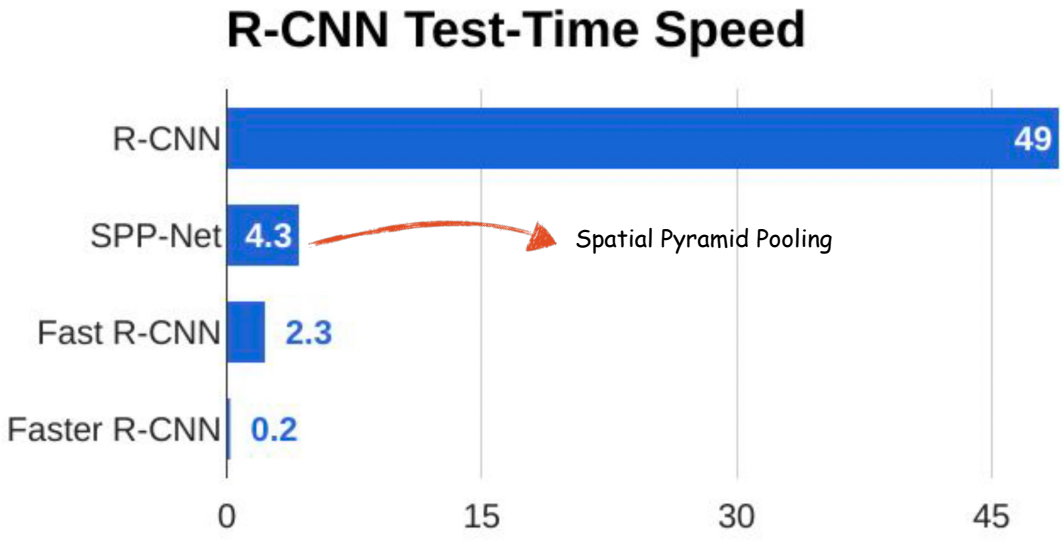
R-CNNs: Comparison

http://cs231n.stanford.edu/slides/2023/lecture_11.pdf



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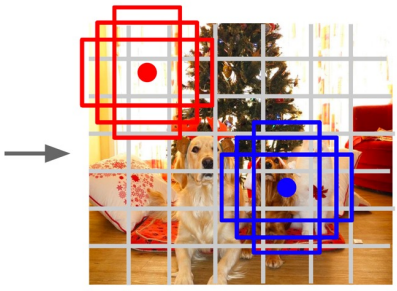
Single-Stage Detection: YOLO

http://cs231n.stanford.edu/slides/2023/lecture_11.pdf

Input image
3 x H x W



Divide image into grid
7 x 7

Image a set of **base boxes** centered at each grid cell
Here B = 3

Within each grid cell:

- Regress from each of the B base boxes to a final box with 5 numbers: (dx, dy, dh, dw, confidence)
- Predict scores for each of C classes (including background as a class)
- Looks a lot like RPN, but category-specific!

Output:
7 x 7 x (5 * B + C)

Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016
Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

YOLO has a lot of versions (v8 now): https://huggingface.co/models?other=yolov8

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YOLO Loss Function

https://www.cs.utexas.edu/~yukez/cs391r_fall2021/slides/pre_09-02_Shivang.pdf

- For YOLO, we need to minimize the following loss
- Sum squared error is used

$$\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

Coordinate Loss: Minimize the difference between x,y,w,h pred and x,y,w,h ground truth. ONLY IF object exists in grid box and if bounding box is resp for pred

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

Confidence Loss: Loss based on confidence ONLY IF there is object

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

No Object Loss based on confidence if there is no object

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} \left(p_i(c) - \hat{p}_i(c) \right)^2$$

Class loss, minimize loss between true class of object in grid box

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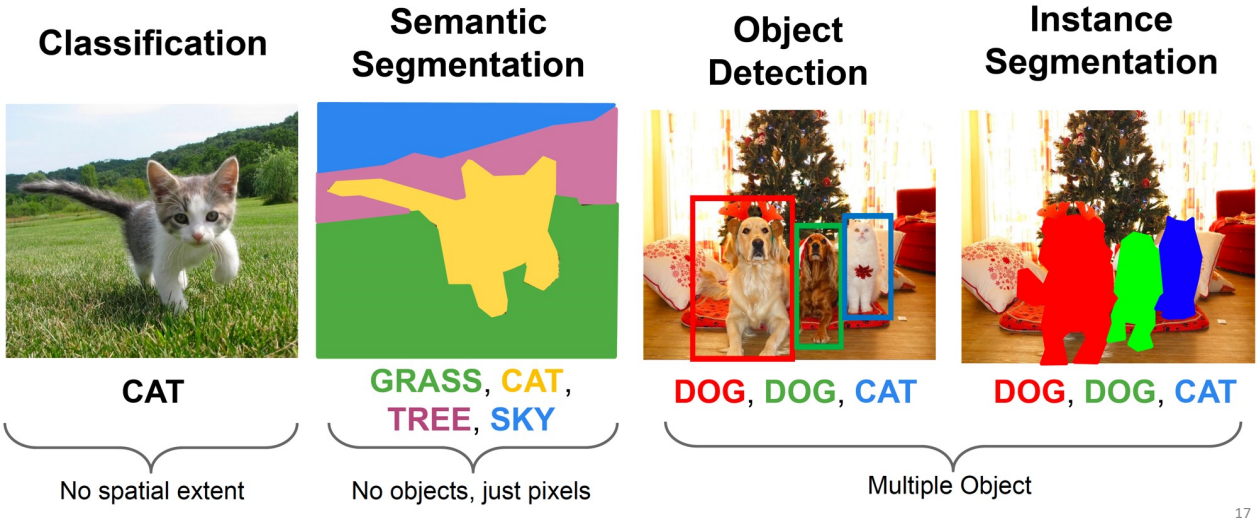
Beyond Boxes: Semantic Segmentation

http://cs231n.stanford.edu/slides/2023/lecture_11.pdf

- Semantic Segmentation: Predict the class of each pixel.



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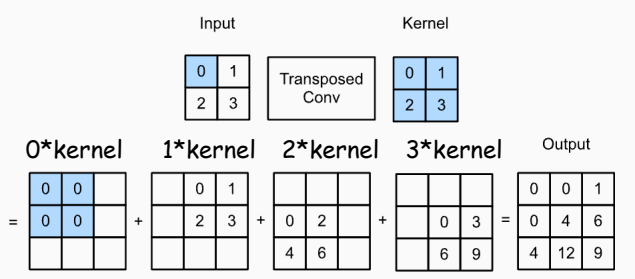
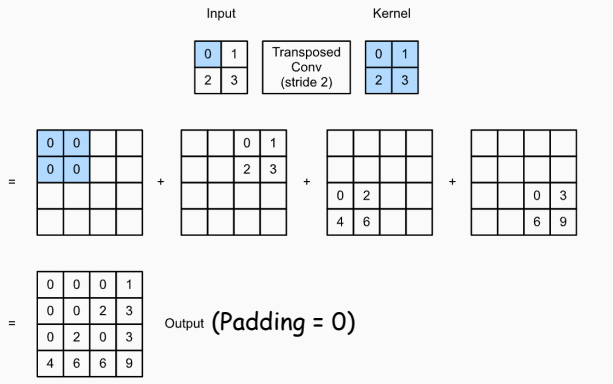
Transposed Convolution

https://www.d2l.ai/chapter_computer-vision/transposed-conv.html

- Transposed Convolution: Increase/upsample the spatial dimensions of convolution.

A guide to convolution arithmetic for deep learning
V Dumoulin, F Visin - arXiv preprint arXiv:1603.07285, 2016 - arxiv.org
… what backwards with respect to the convolution arithmetic chapter, deriving the properties of each transposed convolution by referring to the direct convolution with which it shares the …
☆ 保存 99 引用 被引用次数：2346 相关文章 所有 14 个版本 »





If padding = 1, the first and last rows/columns of the output are removed.

0	2
2	0

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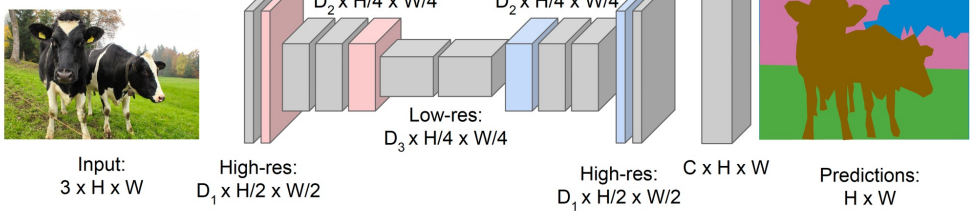
Fully Convolutional Network (FCN)

https://www.d2l.ai/chapter_computer-vision/fcn.html
http://cs231n.stanford.edu/slides/2023/lecture_11.pdf

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!



Fully convolutional networks for semantic segmentation
J Long, E Shelhamer, T Darrell - Proceedings of the IEEE …, 2015 - openaccess.thecvf.com
… for per-pixel tasks like semantic segmentation. We show that a fully convolutional network (FCN) trained end-to-end, pixels-to-pixels on semantic segmentation exceeds the state-of-the-…
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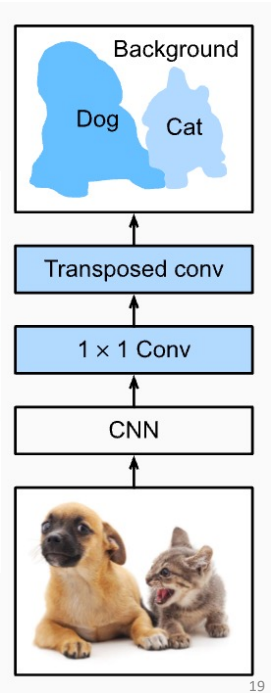

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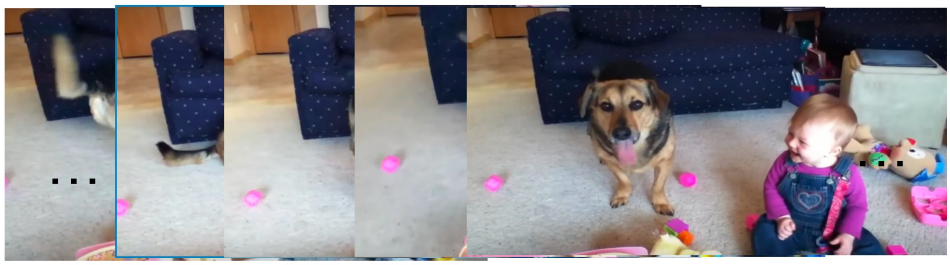
Video = Image x Time

http://cs231n.stanford.edu/slides/2023/lecture_10.pdf

A video is a **sequence** of images
4D tensor: T x 3 x H x W
(or 3 x T x H x W)



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Videos Classification

http://cs231n.stanford.edu/slides/2023/lecture_10.pdf

Input video:
T x 3 x H x W

Swimming
Running
Jumping
Eating
Standing

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Videos Are Big!

http://cs231n.stanford.edu/slides/2023/lecture_10.pdf

Input video:
T x 3 x H x W

Videos are ~30 frames per second (fps)

Size of uncompressed video
(3 bytes per pixel):

SD (640 x 480): **~1.5 GB per minute**
HD (1920 x 1080): **~10 GB per minute**

Solution: Train on short **clips:** low fps and low spatial resolution
e.g. T = 16, H=W=112
(3.2 seconds at 5 fps, 588 KB)

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Training on Clips

http://cs231n.stanford.edu/slides/2023/lecture_10.pdf

Raw video: Long, high FPS

Training: Train model to classify short **clips** with low FPS

Testing: Run model on different clips, average predictions

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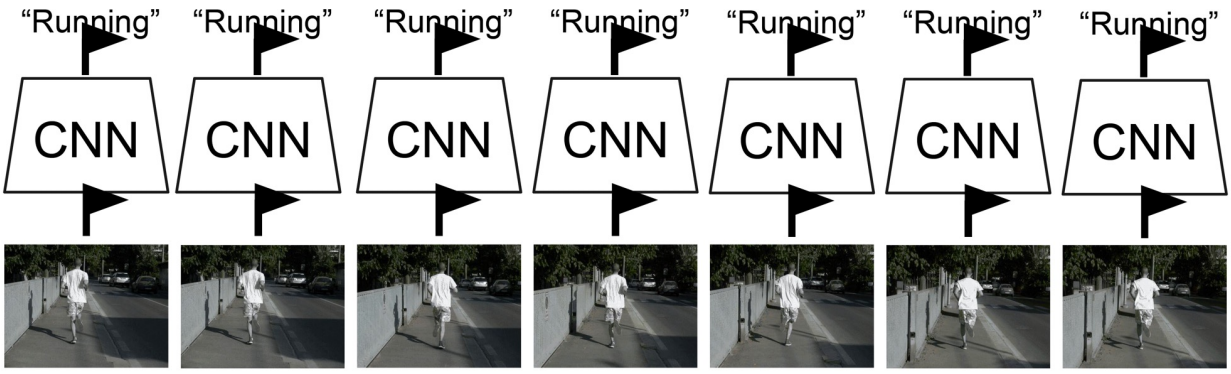
A Strong Baseline: Single Frame CNN

http://cs231n.stanford.edu/slides/2023/lecture_10.pdf

- Train a normal 2D CNN to classify video frames independently; average the predicted probs in testing.



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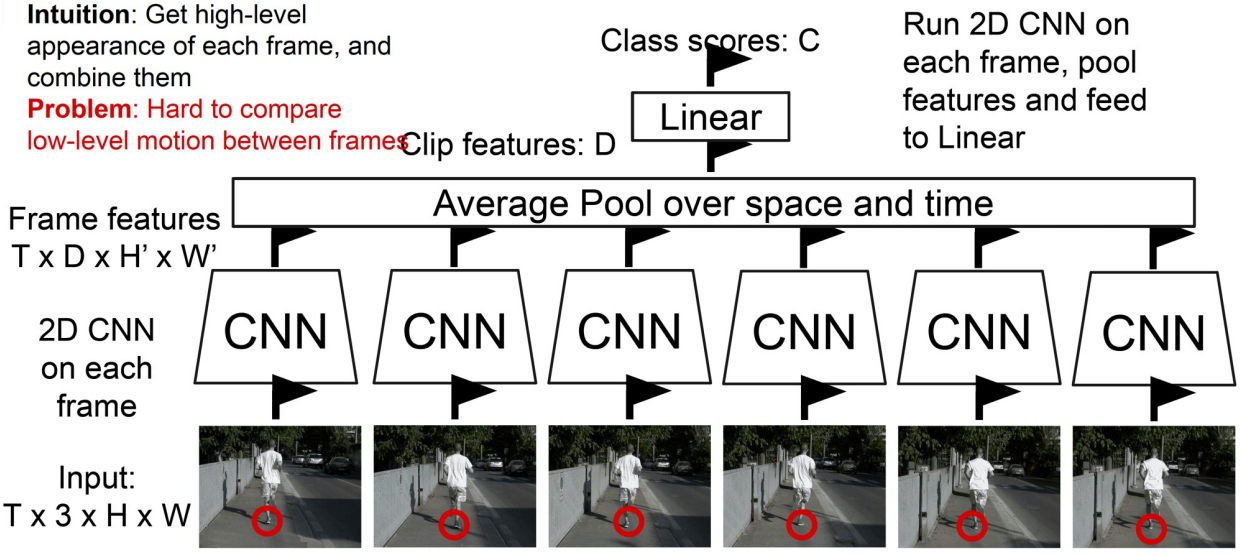
Late Fusion

http://cs231n.stanford.edu/slides/2023/lecture_10.pdf

Intuition: Get high-level appearance of each frame, and combine them

Problem: Hard to compare low-level motion between frames



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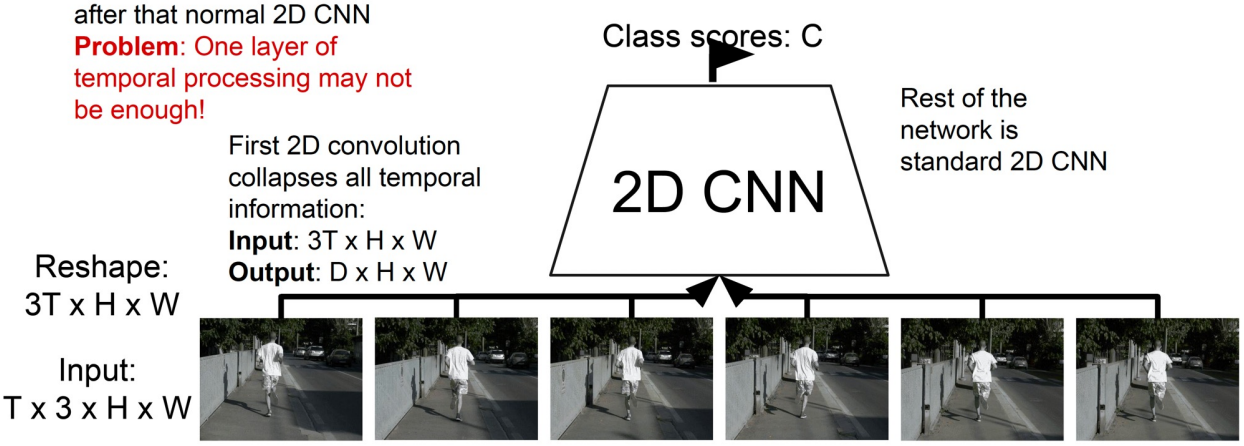
Early Fusion

http://cs231n.stanford.edu/slides/2023/lecture_10.pdf

Large-scale video classification with convolutional neural networks
A Karpathy, G Toderici, S Shetty, T Leung… - Proceedings of the …, 2014 - cv-foundation.org
… performance of CNNs in large-scale video classification, where the networks … video classification benchmarks that match the scale and variety of existing image datasets because …
☆ 保存 99 引用 被引用次数：8299 相关文章 所有 46 个版本 »

Intuition: Compare frames with very first conv layer, after that normal 2D CNN

Problem: One layer of temporal processing may not be enough!



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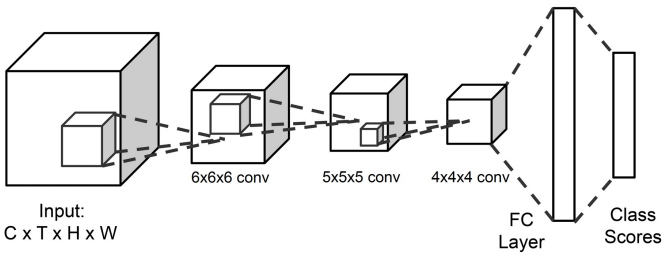
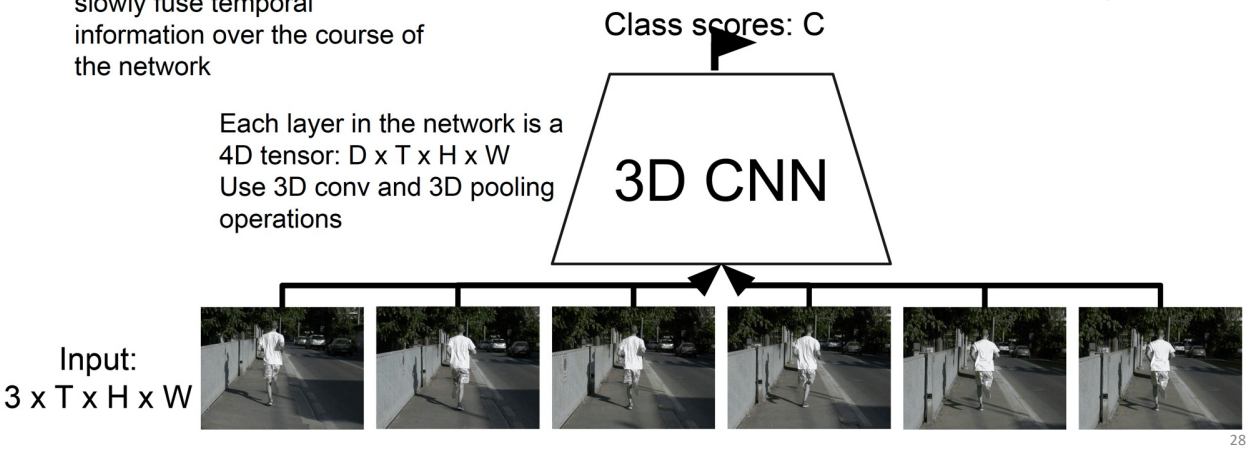
3D CNN

http://cs231n.stanford.edu/slides/2023/lecture_10.pdf

Intuition: Use 3D versions of convolution and pooling to slowly fuse temporal information over the course of the network





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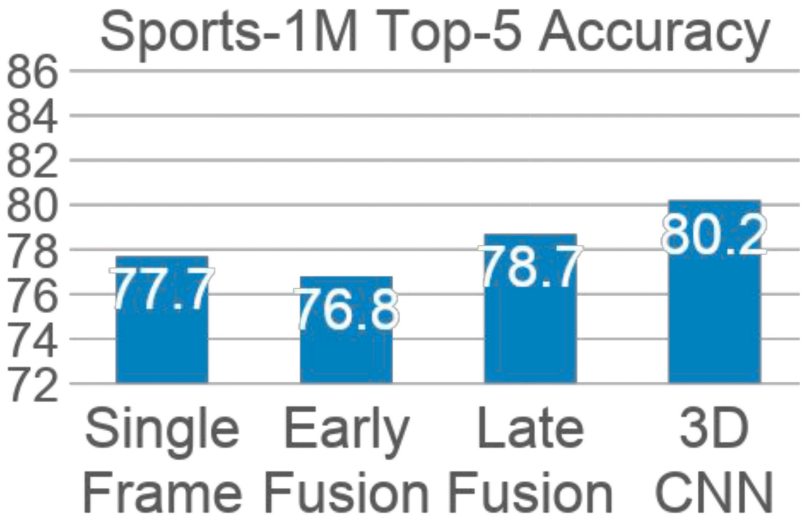
Comparison

http://cs231n.stanford.edu/slides/2023/lecture_10.pdf
Sports-1M dataset: https://github.com/gtoderici/sports-1m-dataset



Single Frame model works well – always try this first!

3D CNNs have improved a lot since 2014!

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Frontiers: Unmasking Social Compliance Behavior During the Pandemic

S Zhang, K Xu, K Srinivasan

Marketing Science, 2023 · pubsonline.informs.org

In 2020, as the novel coronavirus spread globally, face masks were recommended in public settings to protect against and slow down viral transmission. People complied to varying extents, and their reactions may have been driven by a variety of psychological factors. Based on the literature on social influence and on mask-wearing, we define three customer segments: *Fully-Compliant* customers wear masks, and they seem motivated primarily by concerns about their own health risk. *Partially-Compliant* customers also wear masks, but with improper and ineffective coverage; our empirical analysis suggests that they are motivated primarily by a desire to comply with social norms. Finally, *Unmasked* customers do not wear masks. We examine changes in shopping behaviors with the onset of the pandemic to corroborate the conjectured mask-wearing motives. We find that the three groups made significantly different behavior changes: *Fully-Compliant* customers shopped significantly faster and practiced stricter social distancing with the onset of the pandemic, whereas the other two groups did not adjust their shopping duration or social distancing.

History: K. Sudhir served as the senior editor for this article. This paper was accepted through the *Marketing Science*: Frontiers review process.

Funding: Financial support from the National Natural Science Foundation of China [Grants 71622008 and 71832006] and National Social Science Foundation of China [No. 22VRC174] is gratefully acknowledged.

Supplemental Material: The online appendix is available at https://doi.org/10.1287/mksc.2022.1419.

INFORMS

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Social Compliance

- Apply various CV technologies to video clips from security camera of a retail store to classify its customers into fully-compliant, partially-compliant and non-compliant.
- Fully-compliant customers shopped significantly faster and practiced stricter social distancing during the COVID-19 pandemic, whereas the other two groups did not adjust their behaviors.

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Introducing machine-learning-based data fusion methods for analyzing multimodal data: An application of measuring trustworthiness of microenterprises

X Luo, N Jia, E Ouyang, Z Fang

Strategic Management Journal, 2024 · Wiley Online Library

Research Summary

Multimodal data, comprising *interdependent* unstructured text, image, and audio data that collectively characterize the same source, with video being a prominent example, offer a wealth of information for strategy researchers. We emphasize the theoretical importance of capturing the interdependencies between different modalities when evaluating multimodal data. To automate the analysis of video data, we introduce advanced deep machine learning and data fusion methods that comprehensively account for all intra- and inter-modality interdependencies. Through an empirical demonstration focused on measuring the trustworthiness of grassroots sellers in live streaming commerce on Tik Tok, we highlight the crucial role of interpersonal interactions in the business success of microenterprises. We provide access to our data and algorithms to facilitate data fusion in strategy research that relies on multimodal data.

Managerial Summary

Our study highlights the vital role of both verbal and nonverbal communication in attaining strategic objectives. Through the analysis of multimodal data—incorporating text, images, and audio—we demonstrate the essential nature of interpersonal interactions in bolstering trustworthiness, thus facilitating the success of microenterprises. Leveraging advanced machine learning techniques, such as data fusion for multimodal data and explainable artificial intelligence, we notably enhance predictive accuracy and theoretical interpretability in assessing trustworthiness. By bridging strategic research with cutting-edge computational techniques, we provide practitioners with actionable strategies for enhancing communication effectiveness and fostering trust-based relationships. Access our data and code for further exploration.

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Data Fusion to Measure Trustworthiness

- Use DNN (CNN, Recurrent-CNN) to analyze the multi-modal video data (video, verbal, and audio) on TikTok e-commerce.
- Trustworthiness (of grassroots sellers) is measured using crowd-sourced labels.
- Multi-modal data fusion improves the prediction accuracy and theoretical interpretability of seller trustworthiness.

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