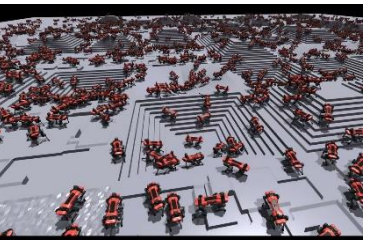
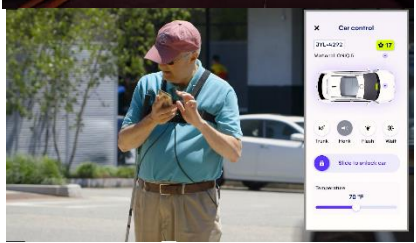
# EC500: Robot Learning and Vision for Navigation




Eshed Ohn-Bar

Feb 21, 2023



bit.ly/3IqZbN2

# Syllabus – plan. Guidelines projec.

**Tentative Schedule**

| Date | Topic | Notes | |
|---|---|---|---|
| 1/23 | Introduction: Why Navigation? | HW0: Due 1/25 | |
| 1/25 | Deep Imitation Learning | | |
| 1/30 | Deep Imitation Learning | HW1: Due in 2 weeks | |
| 2/1 | Affordances and Direct Perception | | |
| 2/6 | Dynamics and Localization | | |
| 2/8 | Semantic Scene Understanding | | |
| 2/13 | Semantic Scene Understanding | HW2: Due in 2 weeks | |
| 2/15 | Object Detection and Tracking | | |

On Feb 27, at 11:59PM or earlier, you should submit a project proposal on blackboard. This should explain explicitly and clearly what you will do. In particular, the proposal should include:

- An abstract: a paragraph with describes the research problem, and an overview of the planned project.
- A list of at least 4 project milestones, and deadlines to achieve them.
- A list of questions to be answered during the project and discussed in the report.
- Describe which datasets/code will you utilize (if there's an existing one for your project).
- A few recent and very closely related papers that you will build on, with full bibliographic data.

https://www.overleaf.com/latex/templates/ieee-conference-template/grfzhhncsfqn

# Robot Learning and Vision for Navigation

## Exercise 2 – Modular Pipeline

Release date: Thursday, 21 Feb. 2023 - **Deadline for Homework: Monday, 13 Mar. 2023 - 23:59**

For this exercise you need to submit a **.zip** folder containing your report as a **.pdf** file (up to 5 pages) and your **.py** code files.

As in the previous exercise, please use the provided code templates. Add your best choice of parameters to the `modular_pipeline.py` file.

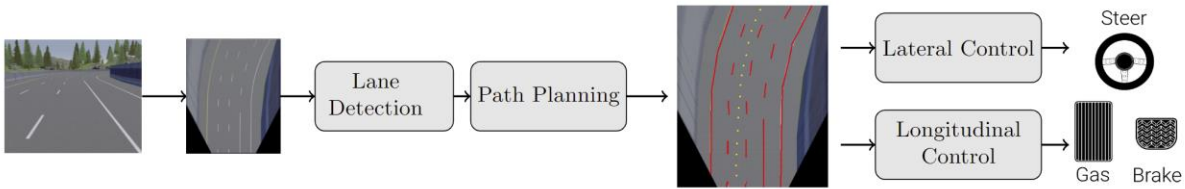



Figure 1: Modular pipeline consisting of a lane detection module, path planning and a control unit.

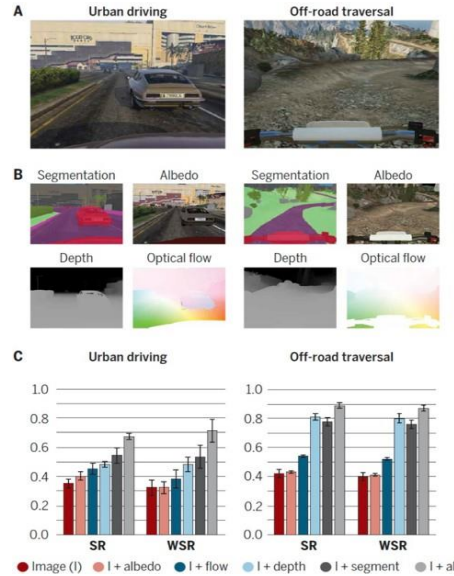
Recap

- History and technological revolutions
- Paradigms for sensorimotor learning
- Deep imitation learning
- Behavior cloning and catastrophic failure
- Dagger and data augmentation methods
- Direct perception
- **Today**: Starting Modular Pipelines

# Does Computer Vision Matter for Action?

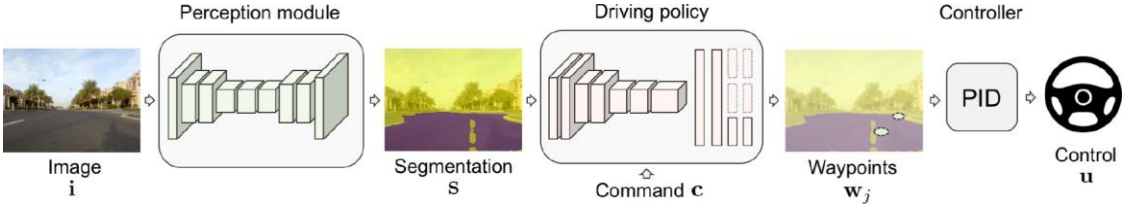
Does Computer Vision Matter for Action?

- ► Analyze various intermediate representations: segmentation, depth, normals, flow…
- ► Intermediate representations improve results
- ► Consistent gains across simulations / tasks
- ► Depth and semantic provide largest gains
- ► Better generalization performance




Zhou, Kra¨henbu¨hl and Koltun: Does computer vision matter for action? Science Robotics, 2019.

# Driving Policy Transfer: Overview




**Problem:**

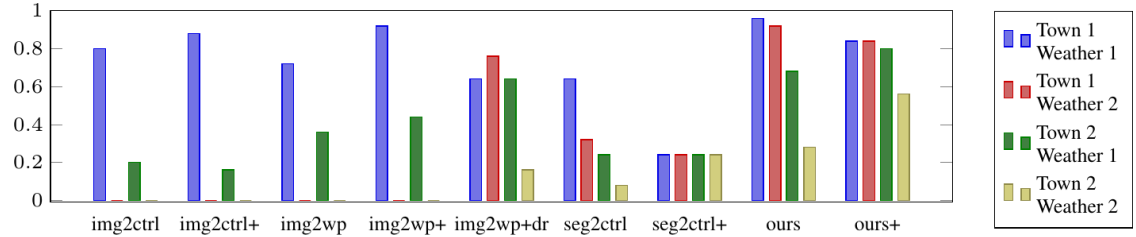
- Driving policies learned in simulation often do not transfer well to the real world

**Idea:**

- Encapsulate driving policy such that it is not directly exposed to raw perceptual input or low-level control (input: semantic segmentation, output: waypoints)
- Allows for transferring driving policy without retraining or finetuning

Müller, Dosovitskiy, Ghanem and Koltun: Driving Policy Transfer via Modularity and Abstraction. CoRL, 2018.

# Driving Policy Transfer: Results

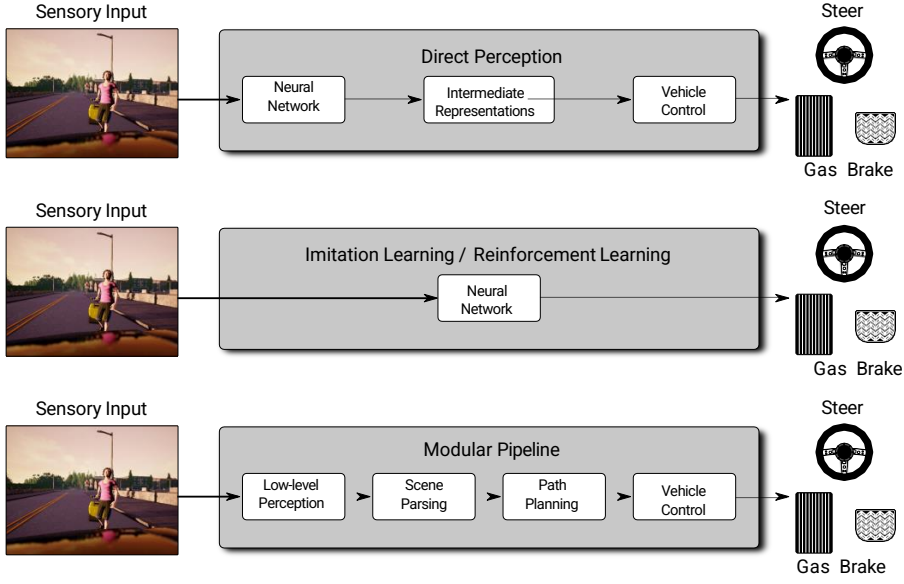



Success Rate over 25 Navigation Trials

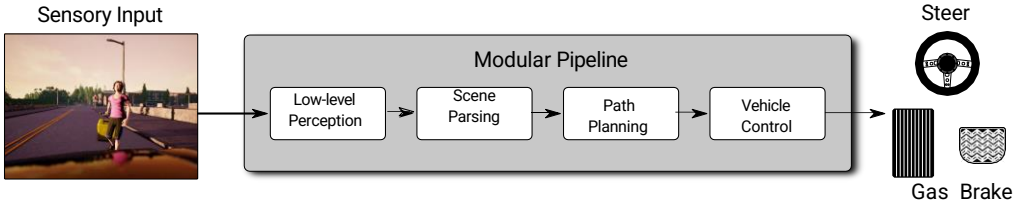
- Driving policy: Conditional Imitation Learning (branched)
- Training: Expert agent, random initialization, noise injection
- Control: PID for lateral and longitudinal control
- Results: Full method generalizes best ("+" = with data augmentation)

Müller, Dosovitskiy, Ghanem and Koltun: Driving Policy Transfer via Modularity and Abstraction. CoRL, 2018.

# Approaches to Self-Driving



# Modular Pipeline




**1. Low-level Perception**

- Localization, road/lane detection
- Reconstruction, motion, tracking

**2. Scene Parsing**

- Association of objects to lanes
- Higher-level understanding (context)

**3. Path Planning**

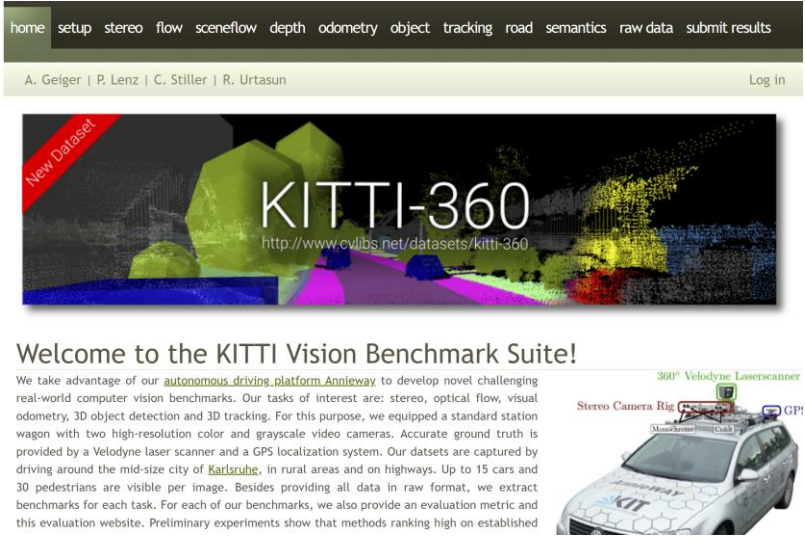
- Route and behavior planning
- Path and trajectory planning

**4. Vehicle Control**

- Kinematic/dynamic vehicle model
- Longitudinal/lateral vehicle control

KITTI Dataset

https://www.cvlibs.net/datasets/kitti/



https://www.cvlibs.net/datasets/kitti/

# Object Detection and Orientation Estimation Evaluation

## Cars

| | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 1 | VoCo | | | **97.11 %** | 98.25 % | **94.46 %** | 0.1 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| 2 | VirConv-S | | | 96.46 % | 96.99 % | 93.74 % | 0.09 s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| 3 | GraR-Vol | | code | 96.29 % | 96.81 % | 91.06 % | 0.07 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| | H. Yang, Z. Liu, X. Wu, W. Wang, W. Qian, X. He and D. Cai: Graph R-CNN: Towards Accurate 3D Object Detection with Semantic-Decorated Local Graph. ECCV 2022. | | | | | | | | |
| 4 | GraR-Po | | code | 96.09 % | 96.83 % | 90.99 % | 0.06 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| | H. Yang, Z. Liu, X. Wu, W. Wang, W. Qian, X. He and D. Cai: Graph R-CNN: Towards Accurate 3D Object Detection with Semantic-Decorated Local Graph. ECCV 2022. | | | | | | | | |
| 5 | NIV-SSD | | | 96.06 % | 96.89 % | 88.63 % | 0.03 s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| 6 | SFD | | code | 96.05 % | **98.95 %** | 90.96 % | 0.1 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| | X. Wu, L. Peng, H. Yang, L. Xie, C. Huang, C. Deng, H. Liu and D. Cai: Sparse Fuse Dense: Towards High Quality 3D Detection with Depth Completion. CVPR 2022. | | | | | | | | |
| 7 | VPFNet | | code | 96.04 % | 96.63 % | 90.99 % | 0.06 s | 2 cores @ 2.5 Ghz (Python) | ☐ |
| | H. Zhu, J. Deng, Y. Zhang, J. Ji, Q. Mao, H. Li and Y. Zhang: VPFNet: Improving 3D Object Detection with Virtual Point based LiDAR and Stereo Data Fusion. IEEE Transactions on Multimedia 2022. | | | | | | | | |
| 8 | VirConv-T | | | 96.01 % | 98.64 % | 93.12 % | 0.09 s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| 9 | CASDC | | | 95.97 % | 98.64 % | 92.99 % | 0.1 s | 1 core @ 2.5 Ghz (Python) | ☐ |
| 10 | TED | | code | 95.96 % | 96.63 % | 93.24 % | 0.1 s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| | H. Wu, C. Wen, W. Li, R. Yang and C. Wang: Transformation-Equivariant 3D Object Detection for Autonomous Driving. AAAI 2023. | | | | | | | | |
| 11 | RDIoU | | code | 95.95 % | 98.77 % | 90.90 % | 0.03 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| | H. Sheng, S. Cai, N. Zhao, B. Deng, J. Huang, X. Hua, M. Zhao and G. Lee: Rethinking IoU-based Optimization for Single- stage 3D Object Detection. ECCV 2022. | | | | | | | | |
| 12 | ACF-Net | | | 95.95 % | 96.64 % | 93.17 % | n/a s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| 13 | CLOCs | | code | 95.93 % | 96.77 % | 90.93 % | 0.1 s | 1 core @ 2.5 Ghz (Python) | ☐ |
| | S. Pang, D. Morris and H. Radha: CLOCs: Camera-LiDAR Object Candidates Fusion for 3D Object Detection . 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) 2020. | | | | | | | | |

# Good old days

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| OC-DPM | | | 64.42 % | 73.50 % | 52.40 % | 10 s | 8 cores @ 2.5 Ghz (Matlab) |

ik, M. Stark, P. Gehler and B. Schiele: Occlusion Patterns for Object Class Detection. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2013.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| LSVM-MDPM-sv | | | 55.77 % | 67.27 % | 43.59 % | 10 s | 4 cores @ 3.0 Ghz (C/C++) |

ger, C. Wojek and R. Urtasun: Joint 3D Estimation of Objects and Scene Layout. NIPS 2011.

enszwalb, R. Girshick, D. McAllester and D. Ramanan: Object Detection with Discriminatively Trained Part-Based Models. PAMI 2010.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| DPM-C8B1 | | | 50.32 % | 59.51 % | 39.22 % | 15 s | 4 cores @ 2.5 Ghz (Matlab + C/C++) |

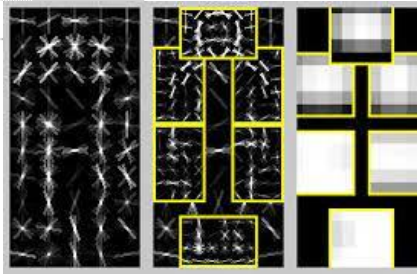
nous submission

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| AOG | | | 36.87 % | 44.41 % | 30.29 % | 3 s | 4 cores @ 2.5 Ghz (Matlab) |

nous submission

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| SVM-Res | | | 30.38 % | 35.02 % | 24.87 % | 10 s | 4 cores @ 2.5 Ghz (Matlab) |

nous submission



# Object Detection and Orientation Estimation Evaluation

## Cars

| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 1 | SubCat | | | 64.94 % | 80.92 % | 50.03 % | 0.3 s | 6 cores @ 2.5 Ghz (Matlab + C/C++) | |

E. Ohn-Bar and M. Trivedi: Learning to Detect Objects at Multiple Orientations and Occlusion Levels. Under submission 2014.

| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 2 | OC-DPM | | | 64.42 % | 73.50 % | 52.40 % | 10 s | 8 cores @ 2.5 Ghz (Matlab) | |

B. Pepik, M. Stark, P. Gehler and B. Schiele: Occlusion Patterns for Object Class Detection. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2013.

| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 3 | LSVM-MDPM-sv | | | 55.77 % | 67.27 % | 43.59 % | 10 s | 4 cores @ 3.0 Ghz (C/C++) | |

A. Geiger, C. Wojek and R. Urtasun: Joint 3D Estimation of Objects and Scene Layout. NIPS 2011.

P. Felzenszwalb, R. Girshick, D. McAllester and D. Ramanan: Object Detection with Discriminatively Trained Part-Based Models. PAMI 2010.

| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 4 | DPM-C8B1 | | | 50.32 % | 59.51 % | 39.22 % | 15 s | 4 cores @ 2.5 Ghz (Matlab + C/C++) | |

Anonymous submission

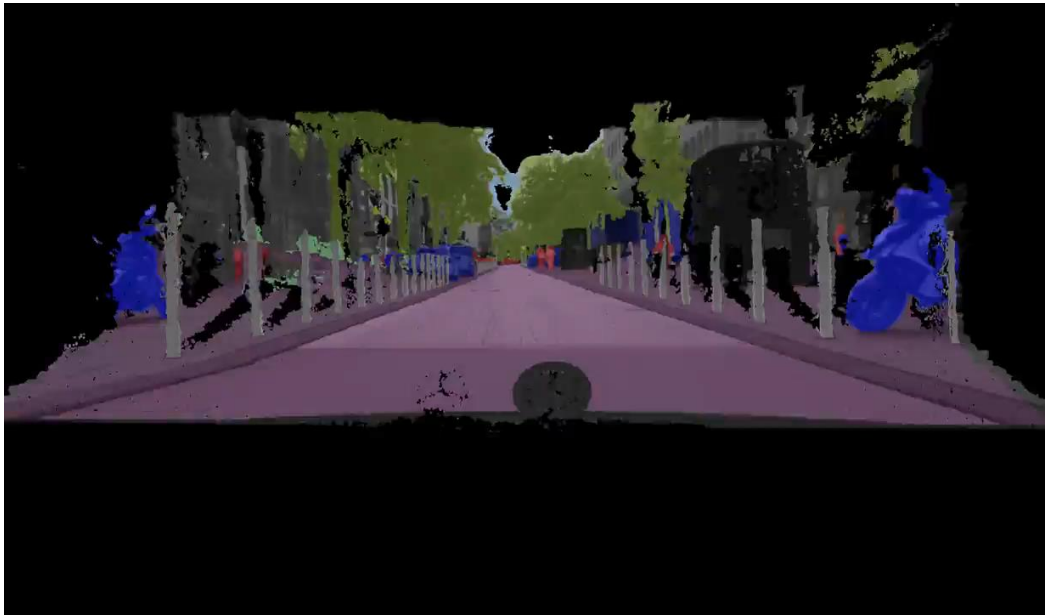
| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 5 | AOG | | | 36.87 % | 44.41 % | 30.29 % | 3 s | 4 cores @ 2.5 Ghz (Matlab) | |

Anonymous submission

| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 6 | SVM-Res | | | 30.38 % | 35.02 % | 24.87 % | 10 s | 4 cores @ 2.5 Ghz (Matlab) | |

Anonymous submission

Cityscapes Dataset



# NuScenes Dataset

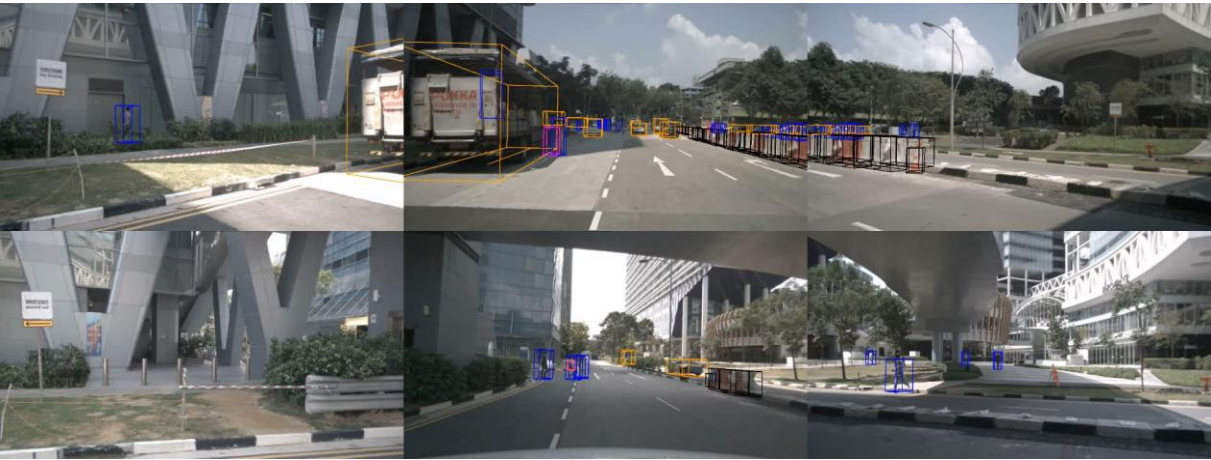
## nuScenes:
## A multimodal dataset for autonomous driving

H. Caesar, V. Bankit, A. Lang, S. Vora, V. E. Liong, Q. Xu, A. Krishnan, Y. Pan, G. Baldan, O. Beijbom

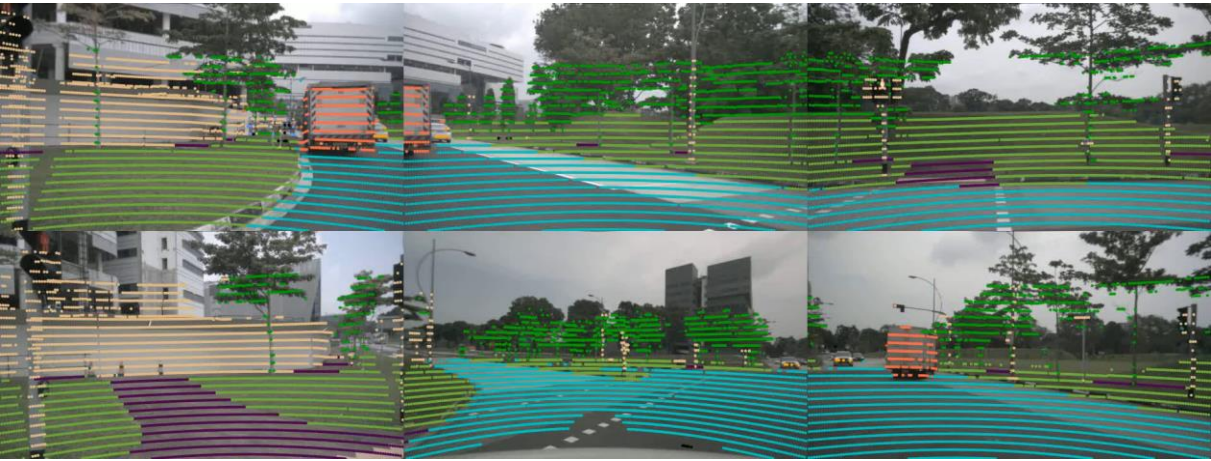

APTIV

# NuScenes Dataset

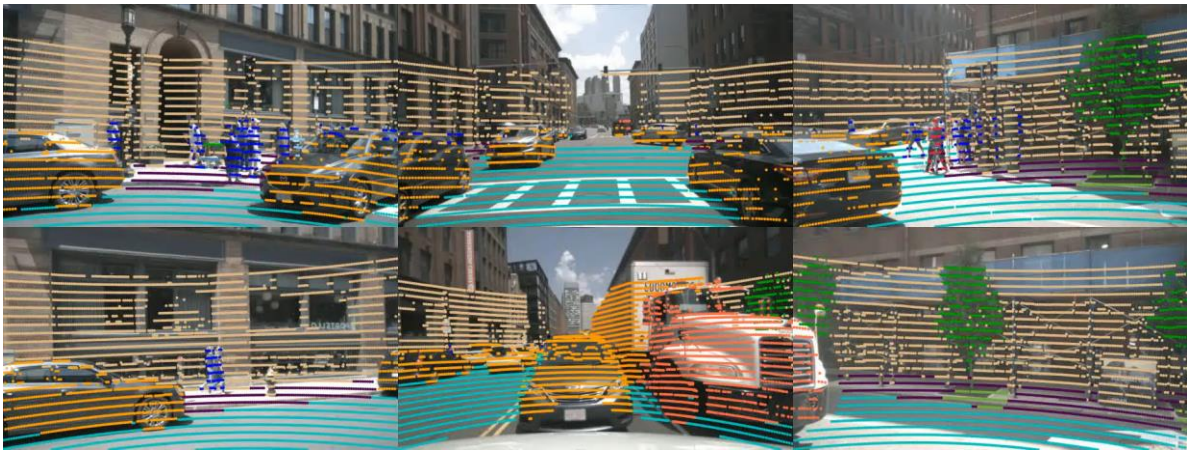
# NuScenes Dataset



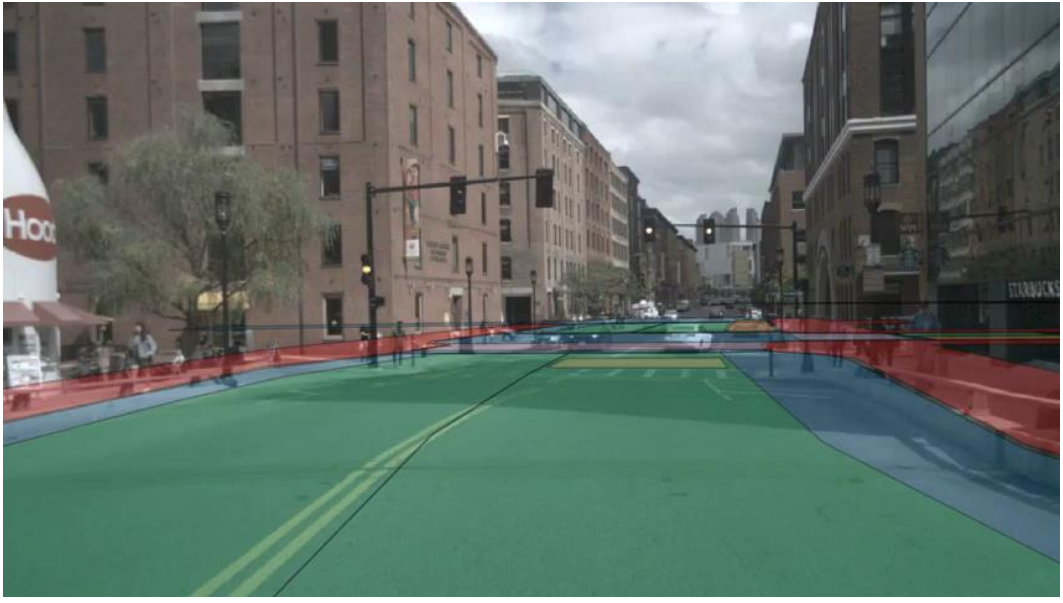
# NuScenes Dataset



# NuScenes Dataset



NuScenes Dataset



# Road and Lane Detection

(some slides adopted from Andres Geiger)

- State-of-the-art commercial systems
- Representations
- Ambiguities
- Lane Marking Detection
- Lane Detection
- Road Segmentation
- Driving Corridor Prediction
- Freespace Estimation

# Road and Lane Detection: State-of-the-Art

**State-of-the-Art Commercial Systems:**

- **Lane departure warning**
  Driver is warned when beginning to leave the current lane

- **Lane keeping support**
  Driver is assisted with minimal steering interventions

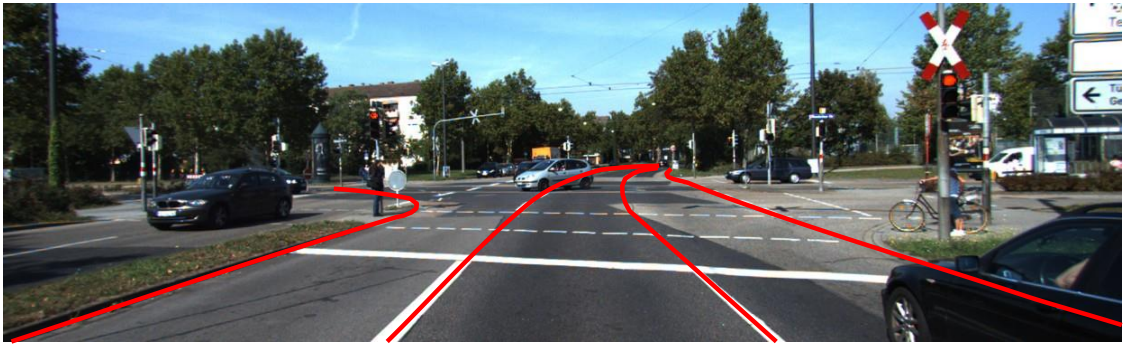
- **Lane keeping/lane departure protection**
  Car keeps the present lane autonomously

# Road and Lane Detection: Representations

**Road and Lane Detection:**

- ► Navigate without detailed global map by sensing “drivable areas” in vicinity of car
- ► Multiple cues available (geometric, semantic, and man-made cues)
- ► Input: image / Lidar/ radar. Multiple possible **output representations**

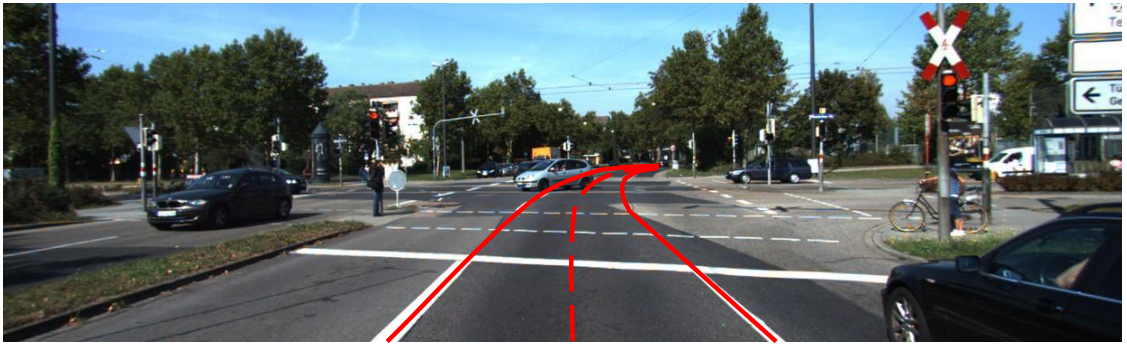
# Road and Lane Detection: Representations



**Lane Marking Detection:**

- Roads are often subdivided into lanes (not everywhere) using lane markings
- Detect lane markings and road curbs; fit parametric model to them
- Steer vehicle based on distance to centerline / lane boundaries

# Road and Lane Detection: Representations



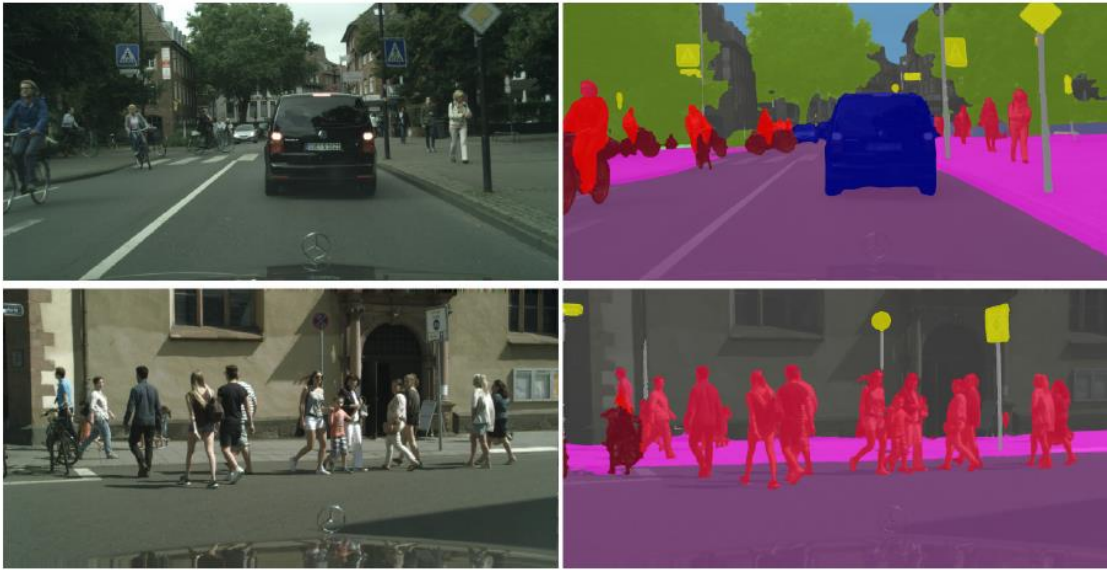
**Lane Detection:**

- Lane detection groups lane markings into lane
- Yields information about lane width and centerline (dashed)
- Navigation relevant lane depends on high-level plan

# Road and Lane Detection: Representations

**Road Segmentation:**

- Classify each pixel in the image as either road or non-road
- Purely semantic cue ("where is a vehicle allowed to drive?")
- Doesn't consider "reachability" / geometry, no information about lanes



# Road and Lane Detection: Representations

**Driving Corridor Prediction:**

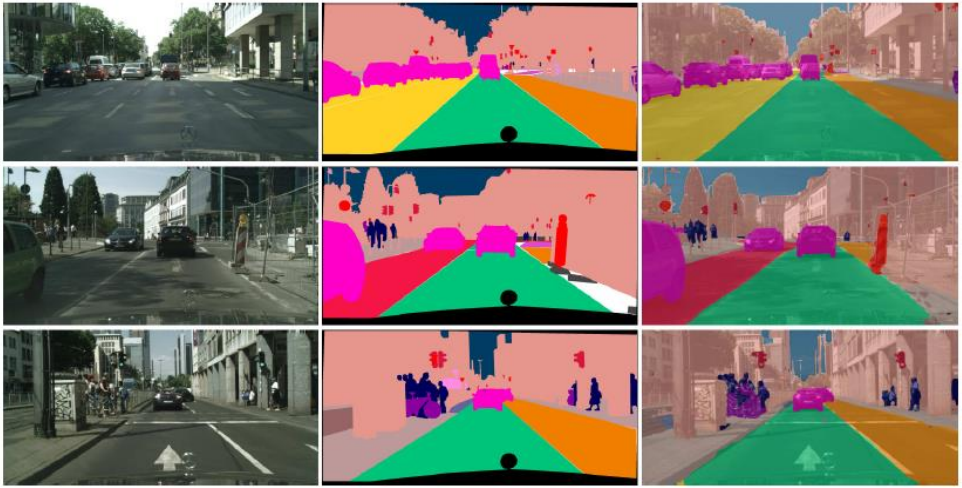
- Estimate the corridor ahead within which the vehicle is supposed to drive
- May or may not consider obstacles (green) within the driving corridor
- Multiple driving corridors, the relevant one depends on the high-level plan

# Road and Lane Detection: Representations

**Driving Corridor Prediction:**

- Estimate the corridor ahead within which the vehicle is supposed to drive
- May or may not consider obstacles (green) within the driving corridor
- Multiple driving corridors, the relevant one depends on the high-level plan

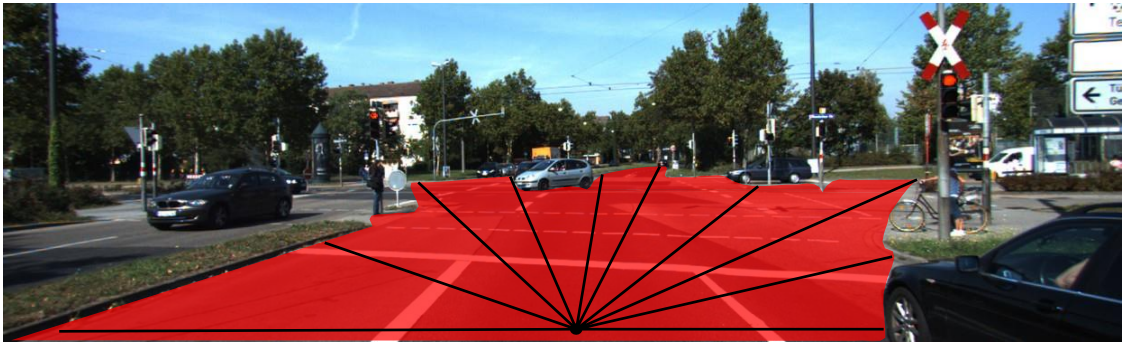
# Driving Corridor Prediction



- Fine-grained semantic segmentation (ego/parallel/opposite lanes)

Meyer, Salscheider, Orzechowski and Christoph Stiller: Deep Semantic Lane Segmentation. IROS, 2018.

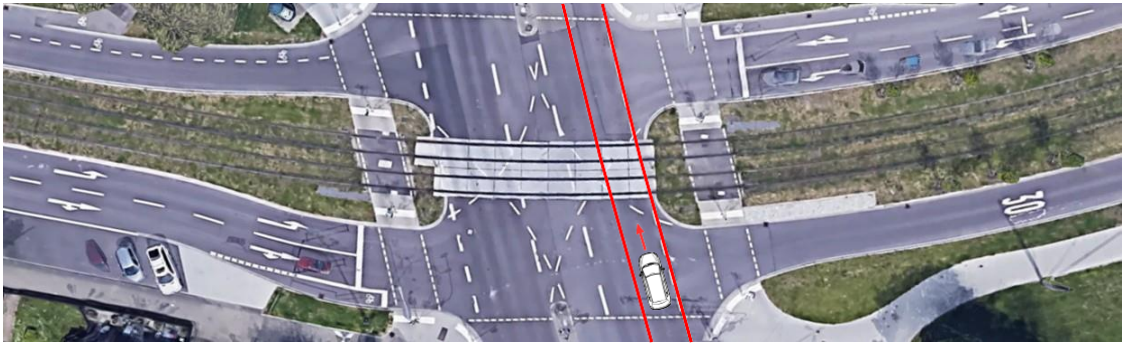
# Road and Lane Detection: Representations



**Freespace Estimation:**

- Estimate places that can be reached without collision
- Purely geometric cue (“which places can be directly reached?”)
- Doesn’t require semantic information or information about lanes ( $\Rightarrow$ robust)

# Road and Lane Detection: Representations



**2D vs. 3D Representation:**

- Estimating quantities in the 2D image domain is not directly useful
- Needs to be mapped into 3D (or bird's eye view) where vehicle is controlled
- Given an estimate of the road surface (e.g., 3D plane), this is possible

# Road and Lane Detection: Ambiguities

**Observations can be ambiguous:**

- This is an easier case (similar to highway driving)
- Road segmentation, lane boundaries and driving corridor clearly defined
- Freespace Estimation: is the grass field on the right traversable or not?

# Road and Lane Detection: Ambiguities


**Observations can be ambiguous:**

- Temporary lane markings during road construction, often old ones not erased
- Which lane marking counts? Which ones are relevant (here: bicycle lane?)
- Lane markings often hard to detect (visibility), demaged or missing

# Road and Lane Detection: Ambiguities


**Observations can be ambiguous:**

- Road Segmentation: which parts are considered road? (vs. sidewalk etc.)
- Freespace Estimation: is the sidewalk drivable? (height threshold)
- Lane Boundary Detection: neither lane markings nor curbs in this image

# Road and Lane Detection: Ambiguities

**Observations can be ambiguous:**

- Navigation in parking lots not possible based on lane markings alone
- Accessibility of entryway (left) depends on height of curb (subtle cue)
- Curbs can be of arbitrary height, how to detect them robustly?

# Road and Lane Detection: Ambiguities

**Observations can be ambiguous:**

- Rural streets often unmarked, lane detection very difficult
- Detection of road signs relevant to determine allowed driving directions
- Sometimes difficult to detect if car is parked or not (affecting driving corridor)

# Road and Lane Detection: Ambiguities

**Observations can be ambiguous:**

- Often very unstructured environments which are hard to capture parametrically
- Scene elements sometimes resemble lane markings, but are not
- Some areas not designated for driving, yet not clearly marked (here: poles)

# Road and Lane Detection: Ambiguities

**Observations can be ambiguous:**

- Lane markers often missing at intersections (otherwise too confusing)
- Tram railroad tracks can be confused with lane markings
- Structured but at the same time very unstructured, holistic and reasoning required

# Road and Lane Detection: Ambiguities

**Observations can be ambiguous:**

- Often navigation based solely on lane markings not a good idea
- In particular, construction sites are often badly structured
- Construction signage changes street layout, lanes partially obstructed

# Road and Lane Detection: Ambiguities

**Observations can be ambiguous:**

- Here no lane markings but implicitly two lanes
- However, both lanes narrow down into one based on very subtle cues
- Requires combination of structured planning and reactive control

# Road and Lane Detection: Ambiguities

**Observations can be ambiguous:**

- Sometimes lane markings can have very different semantics
- Allowed driving directions not always easy to infer
- Heavy occlusions might obstruct the sensor field of view

# Road and Lane Detection: Summary

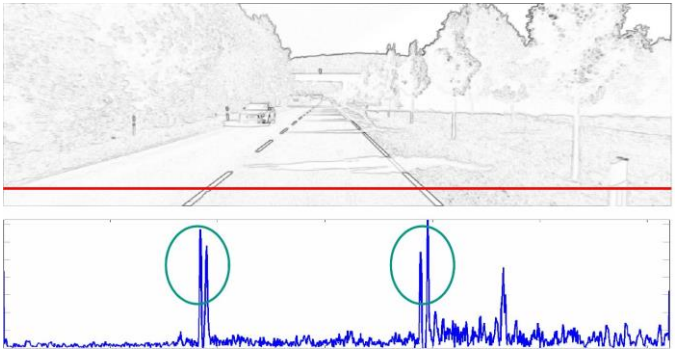
| | **Pros** | **Cons** |
|---|---|---|
| Lane Marking | • Relatively easy inference task<br>• Compact parametric models | • Markings missing/deteriorated<br>• Only in structured env. (highway) |
| Lane | • Directly yields path / centerline<br>• Compact parametric models | • Ambiguous/difficult to estimate<br>• Only in structured env. (highway) |
| Road Segment. | • Works in unstructred env.<br>• Doesn't rely on accurate geometry | • Semantic ambiguities<br>• Doesn't output path information |
| Driving Corridor | • Directly relevant to control<br>• Also comprises obstacle inform. | • Depends on control signal<br>• Ambiguous/difficult to estimate |
| Freespace Est. | • Works in unstructred env.<br>• Doesn't require semantics | • Relies on accurate geometry<br>• Doesn't output path information |

# Lane Marking Detection

# Detection of Lane Markings

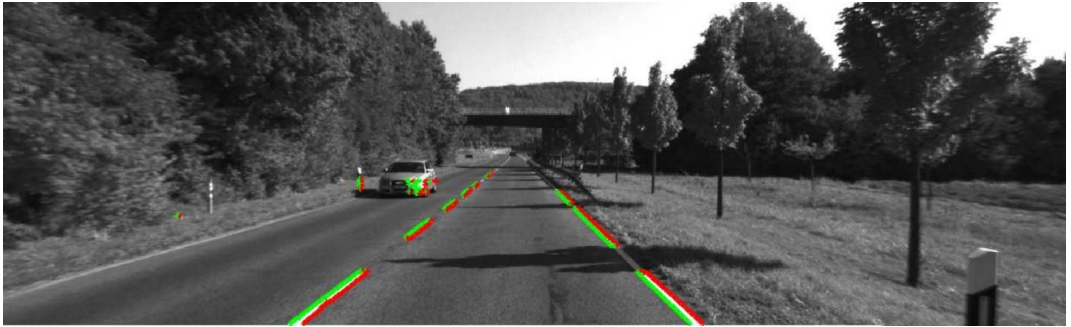
- Gradient Image (convolution with horizontal kernel $k = [-1\ 0\ +1]$)
- Alternatives: steerable filters, templates, learned features

# Detection of Lane Markings



- Search for large gradients along each image row
- If depth available: filter points not on ground plane (e.g., eg by plane fitting)
- Remove isolated points or points for which no opposite gradient exists in vicinity

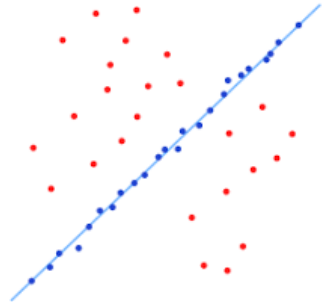
# Detection of Lane Markings



- Green: detected left boundary of lane marking
- Red: detected right boundary of lane marking
- False positives can be rejected using heuristics or robust fitting (e.g., random sample consensus - RANSAC)
- Note: not all lane markings detected!

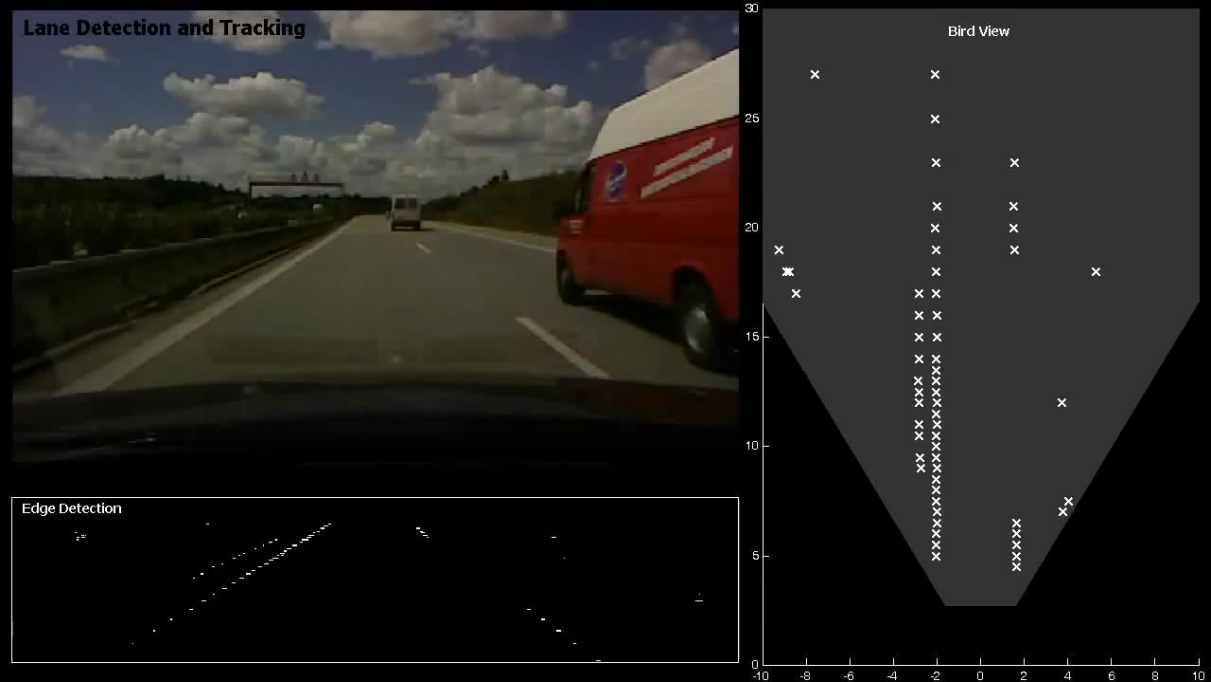
**Algorithm 1** RANSAC

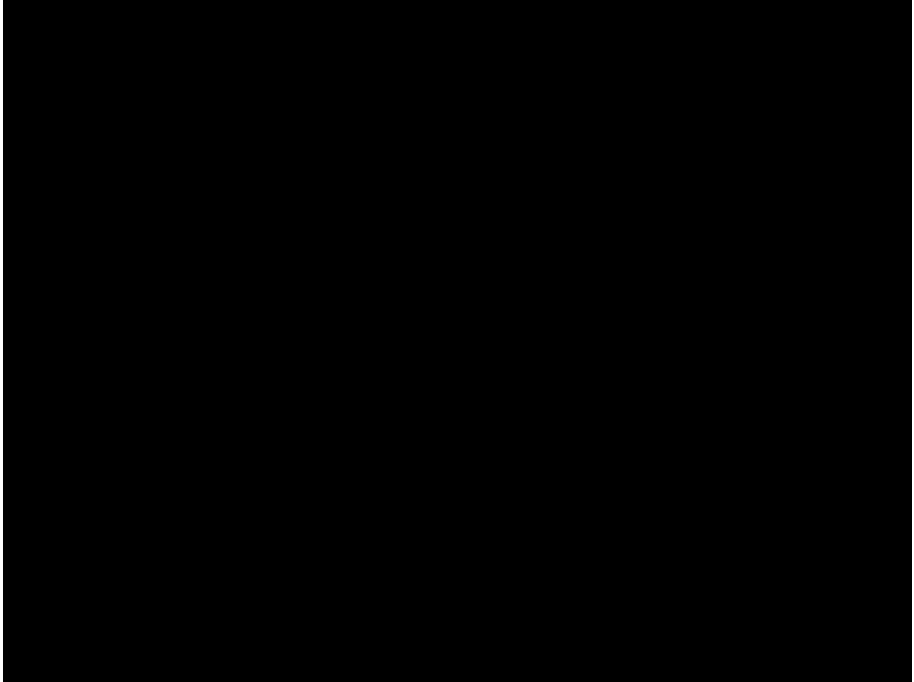
1: Select randomly the minimum number of points required to determine the model parameters.
2: Solve for the parameters of the model.
3: Determine how many points from the set of all points fit with a predefined tolerance $\epsilon$.
4: If the fraction of the number of inliers over the total number points in the set exceeds a predefined threshold $\tau$, re-estimate the model parameters using all the identified inliers and terminate.
5: Otherwise, repeat steps 1 through 4 (maximum of $N$ times).



Inverse Perspective Mapping (IPM)

Main takeaway: estimate 3D position by assuming world is flat


Lane Detection and Tracking
Edge Detection
Bird View
30
25
20
15
10
5
0
-10
-8
-6
-4
-2
0
2
4
6
8
10



# Panoramic Bird-eye-view/top-down from a monocular camera (numbers are estimated speeds)

# Inverse Perspective Mapping: Example

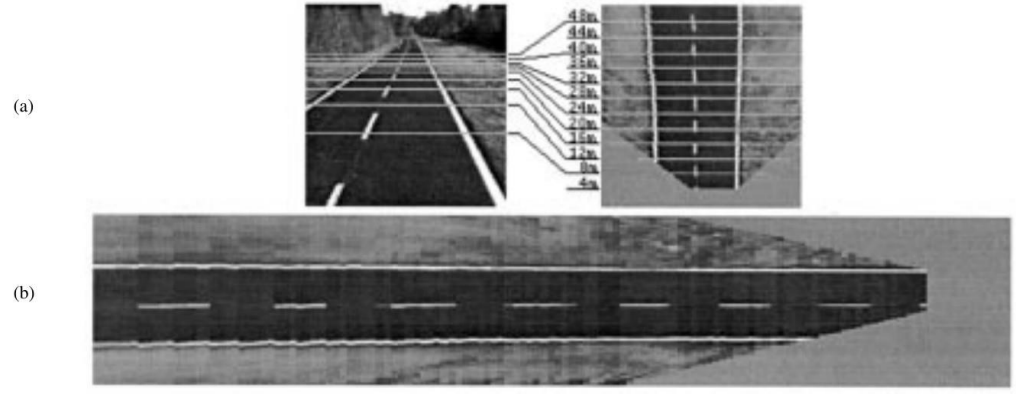
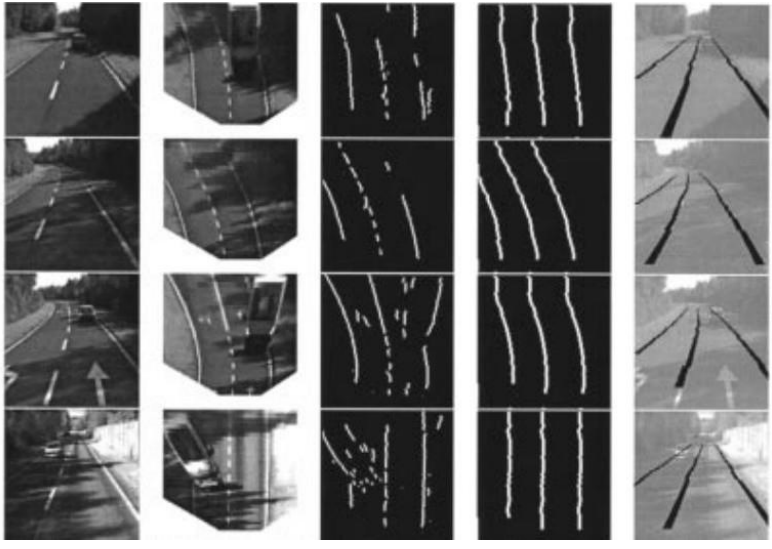



Fig. 8. (a) Horizontal calibration of the MOB-LAB vision system. (b) Rotated version of the remapped image considering an aspect ratio of 1 : 1.

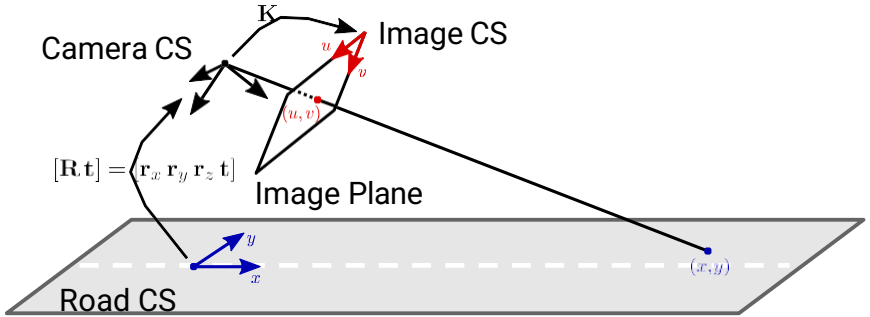
Bertozzi and Broggi: GOLD: a parallel real-time stereo vision system for generic obstacle and lane detection. TIP, 1998.

# Inverse Perspective Mapping: Example



Bertozzi and Broggi: GOLD: a parallel real-time stereo vision system for generic obstacle and lane detection. TIP, 1998.

# Inverse Perspective Mapping (IPM)

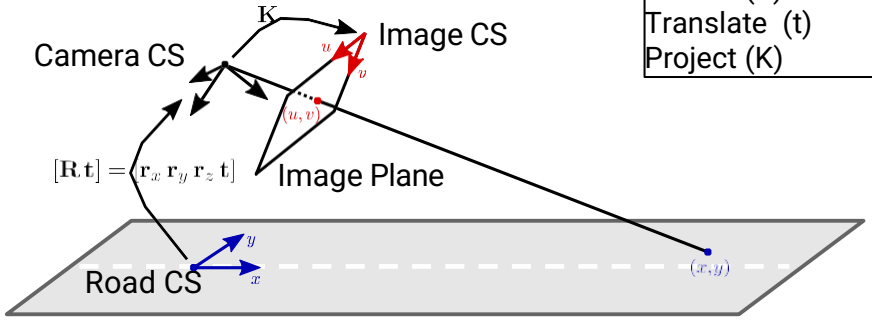



- IPM maps each pixel on the image plane to the respective ground plane point
- IPM is only possible if either per pixel depth or ground model (e.g., plane) known
- How to obtain ground plane (i.e., extrinsic parameters [**R t**])?

Bertozzi and Broggi: GOLD: a parallel real-time stereo vision system for generic obstacle and lane detection. TIP, 1998.

# Inverse Perspective Mapping (IPM)

3D Operations:
Rotate (R)
Translate (t)
Project (K)

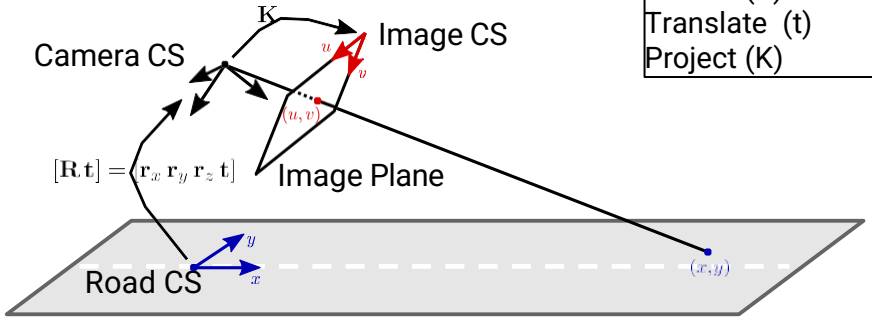



$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \propto \mathbf{K} \begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \overset{z=0}{\Rightarrow} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \propto \mathbf{K} \begin{bmatrix} \mathbf{r}_x & \mathbf{r}_y & \mathbf{t} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \Rightarrow \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \propto \begin{bmatrix} \mathbf{r}_x & \mathbf{r}_y & \mathbf{t} \end{bmatrix}^{-1} \mathbf{K}^{-1} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$

Bertozzi and Broggi: GOLD: a parallel real-time stereo vision system for generic obstacle and lane detection. TIP, 1998.

# Inverse Perspective Mapping (IPM)

3D Operations:
Rotate (R)
Translate (t)
Project (K)




$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \propto \mathbf{K} \begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \overset{z=0}{\Rightarrow} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \propto \mathbf{K} \begin{bmatrix} \mathbf{r}_x & \mathbf{r}_y & \mathbf{t} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \Rightarrow \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \propto \begin{bmatrix} \mathbf{r}_x & \mathbf{r}_y & \mathbf{t} \end{bmatrix}^{-1} \mathbf{K}^{-1} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$

Bertozzi and Broggi: GOLD: a parallel real-time stereo vision system for generic obstacle and lane detection. TIP, 1998.

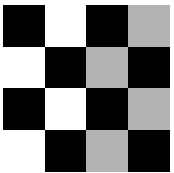
$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \sim \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$

**Homography H (planar projective transformation)**

3x3 Homography matrix

**Punchline: For planar surfaces, 3D to 2D perspective projection reduces to a 2D to 2D transformation.**

**Punchline2: This transformation is INVERTIBLE!**



Whiteboard example

# Parametric Lane Marking Estimation

- Lane marking detection alone is not sufficient (why?)
- Only returns a set of pixels in image or road plane space
- In order to be useful for navigation, this needs to be transformed into a more ***semantically meaningful parametric model***
- Often low-dimensional parametric models (lines, polynomials, bezier curves, splines) are used
  - In the following: splines
- Note 1: This is a multi-model fitting problem!
- Note 2: Outliers must be handled (model must be robust)!

# Parametric Lane Marking Estimation

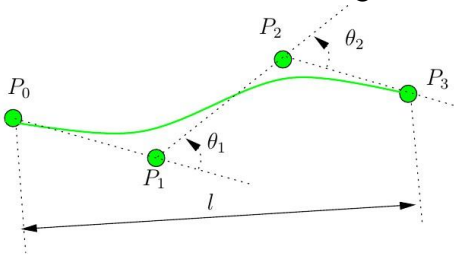



Fig. 7. Spline score computation.

**Algorithm 1** RANSAC Spline Fitting

```
for i = 1 to numIterations do
    points=getRandomSample()
    spline=fitSpline(points)
    score=computeSplineScore(spline)
    if score > bestScore then
        bestSpline = spline
    end if
end for
```

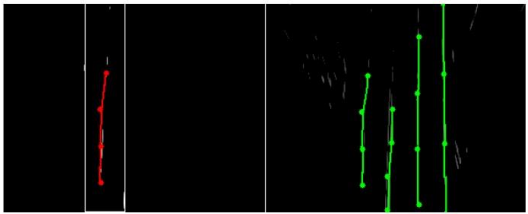


Fig. 8. RANSAC Spline fitting. Left: one of four windows of interest (white) obtained from previous step with detected spline (red). Right: the resulting splines (green) from this step

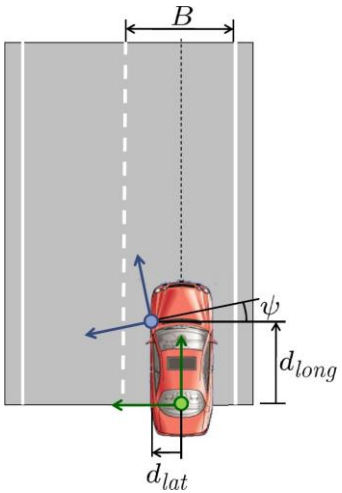
Fig. 10. Post-processing splines. Left: splines before post-processing in blue. Right: splines after post-processing in green. They appear longer and localized on the lanes.

# Parametric Lane Marking Estimation

Aly: Real time detection of lane markers in urban streets. IV, 2008.

Task:
Given model for the lanes,
***Fit it to observed data points***

# Model for Straight Lanes




**Geometric model:** (straight=highway scenario)

- Can we fit a single model for the entire lane?
- Lane width $B \in \mathbb{R}^+$
- Lateral vehicle offset wrt. centerline $d_{lat} \in \mathbb{R}$
- Longitudinal position $d_{long} \in \mathbb{R}$
- Yaw angle $\psi \in [-\pi, \pi]$

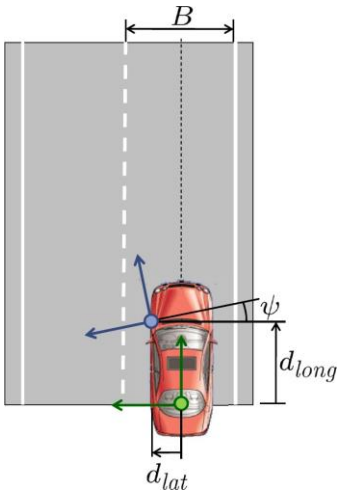
**State:**

$$\mathbf{s} = \begin{bmatrix} B \\ d_{long} \\ d_{lat} \\ \psi \end{bmatrix}$$

**Summary:**

- ►Detect lane markings in camera image
- ►Transform position of markings into vehicle coordinates
- ►Estimate pose parameters and lane width

# Model for Straight Lanes




**Geometric model:** (straight=highway scenario)

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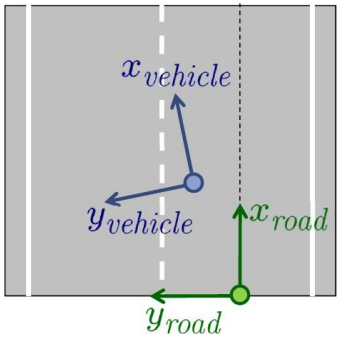
- Lateral vehicle offset wrt. centerline $d_{lat} \in \mathbb{R}$
- Longitudinal position $d_{long} \in \mathbb{R}$
- Yaw angle $\psi \in [-\pi, \pi]$

**State:**

$$\mathbf{s} = \begin{bmatrix} B \\ d_{long} \\ d_{lat} \\ \psi \end{bmatrix}$$

# Model for Straight Lanes

Think rotation and translation




**Transformation vehicle → road coordinates:**

$$\begin{bmatrix} x_{road} \\ y_{road} \end{bmatrix} = \begin{bmatrix} d_{long} \\ d_{lat} \end{bmatrix} + \begin{bmatrix} \cos(\psi) & -\sin(\psi) \\ \sin(\psi) & \cos(\psi) \end{bmatrix} \begin{bmatrix} x_{vehicle} \\ y_{vehicle} \end{bmatrix}$$

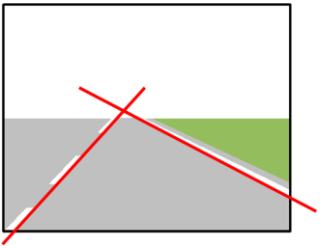
**Transformation road → vehicle coordinates:**

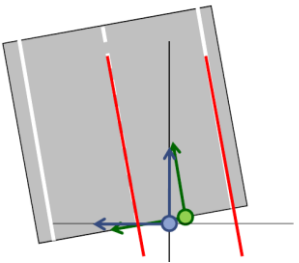
$$\begin{bmatrix} x_{vehicle} \\ y_{vehicle} \end{bmatrix} = \begin{bmatrix} \cos(\psi) & \sin(\psi) \\ -\sin(\psi) & \cos(\psi) \end{bmatrix} \left( \begin{bmatrix} x_{road} \\ y_{road} \end{bmatrix} - \begin{bmatrix} d_{long} \\ d_{lat} \end{bmatrix} \right)$$

# Model for Straight Lanes

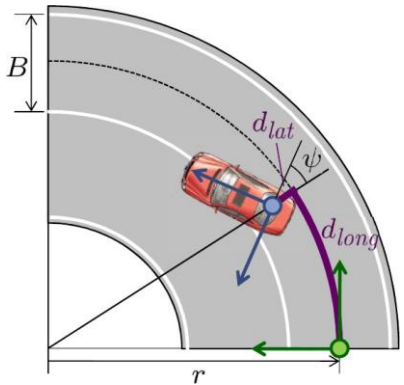
**Summary:**

- Detect lane markings in camera image
- Transform position of markings into vehicle coordinates
- Estimate pose parameters and lane width





# Model for Circular Lanes




**Geometric model:**

- Lane width $B \in \mathbb{R}^+$
- Signed radius $r \in \mathbb{R}$ or curvature $\kappa = \frac{1}{r}$
- Lateral vehicle offset $d_{lat} \in \mathbb{R}$
- Longitudinal position $d_{long} \in \mathbb{R}$
- Yaw angle $\psi \in [-\pi, \pi]$

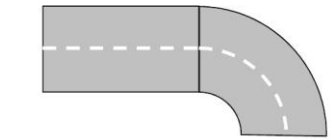
**State:**

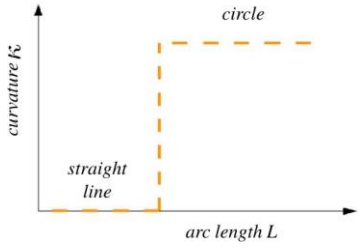
$$\mathbf{s} = \begin{bmatrix} B & r & d_{long} & d_{lat} & \psi \end{bmatrix}^T$$

# Circular trajectories are not enough

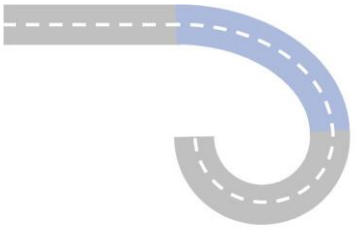
$$y(\ell) \approx \frac{1}{2}\kappa_0\ell^2 + \frac{1}{6}\kappa_1\ell^3$$

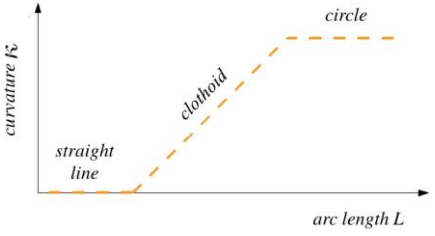
**Circle-Straight Combination**






**Clothoid**





# Deep Convolutional Image Segmentation

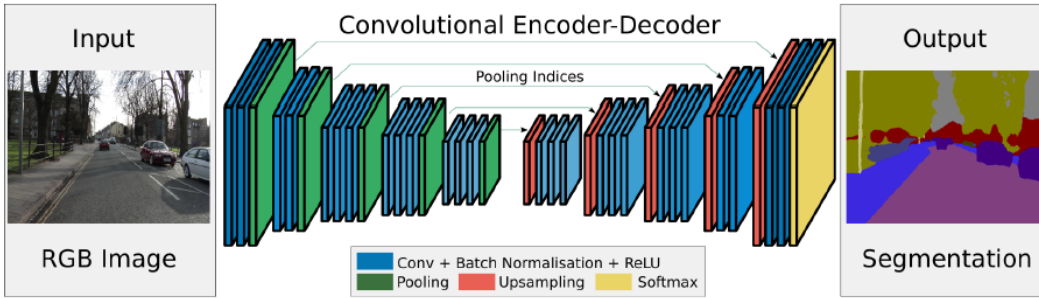



Fig. 2. An illustration of the SegNet architecture. There are no fully connected layers and hence it is only convolutional. A decoder upsamples its input using the transferred pool indices from its encoder to produce a sparse feature map(s). It then performs convolution with a trainable filter bank to densify the feature map. The final decoder output feature maps are fed to a soft-max classifier for pixel-wise classification.

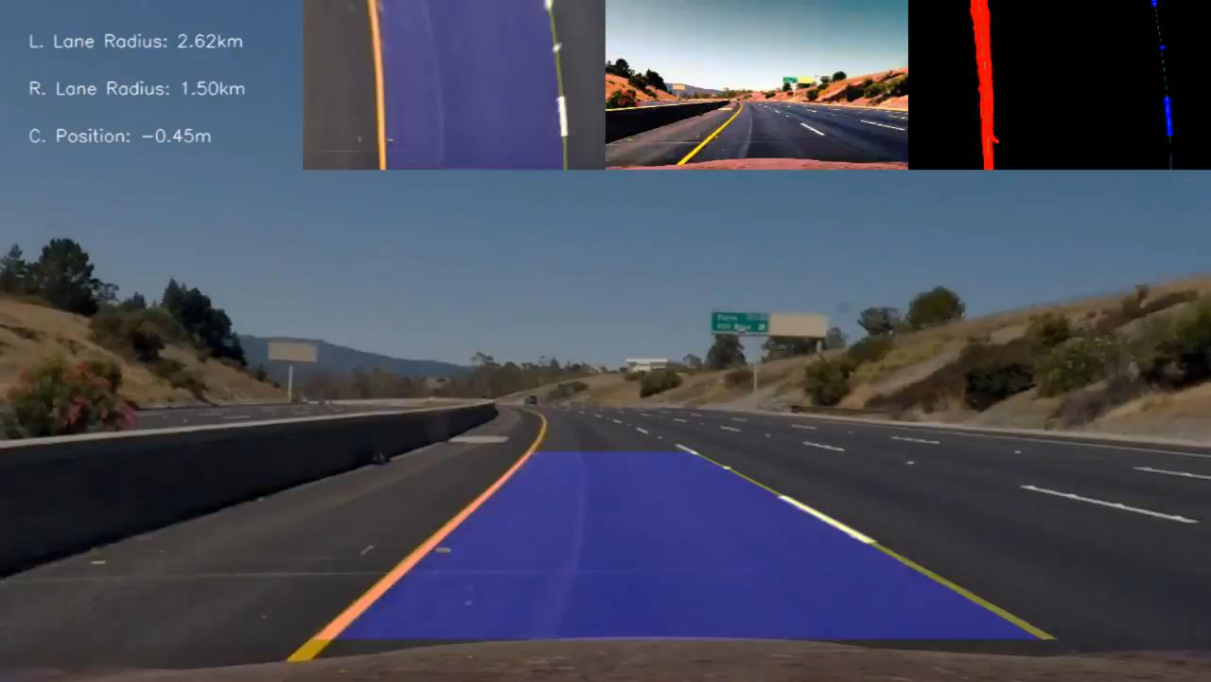
Badrinarayanan, Kendall and Cipolla: SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. PAMI, 2017.

## Further Readings

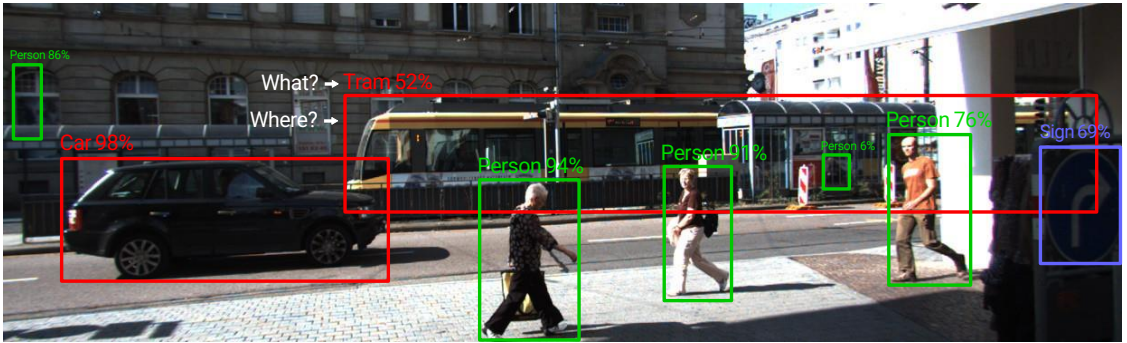
I Aly: Real time detection of lane markers in urban streets. IV, 2008.

I Badrinarayanan, Kendall and Cipolla: SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. PAMI, 2017.

I Badino, Franke and Mester: Free Space Computation Using Stochastic Occupancy Grids and Dynamic Programming. ICCV Workshops, 2007.


L. Lane Radius: 2.62km
R. Lane Radius: 1.50km
C. Position: −0.45m

# Problem Setting – Object Detection



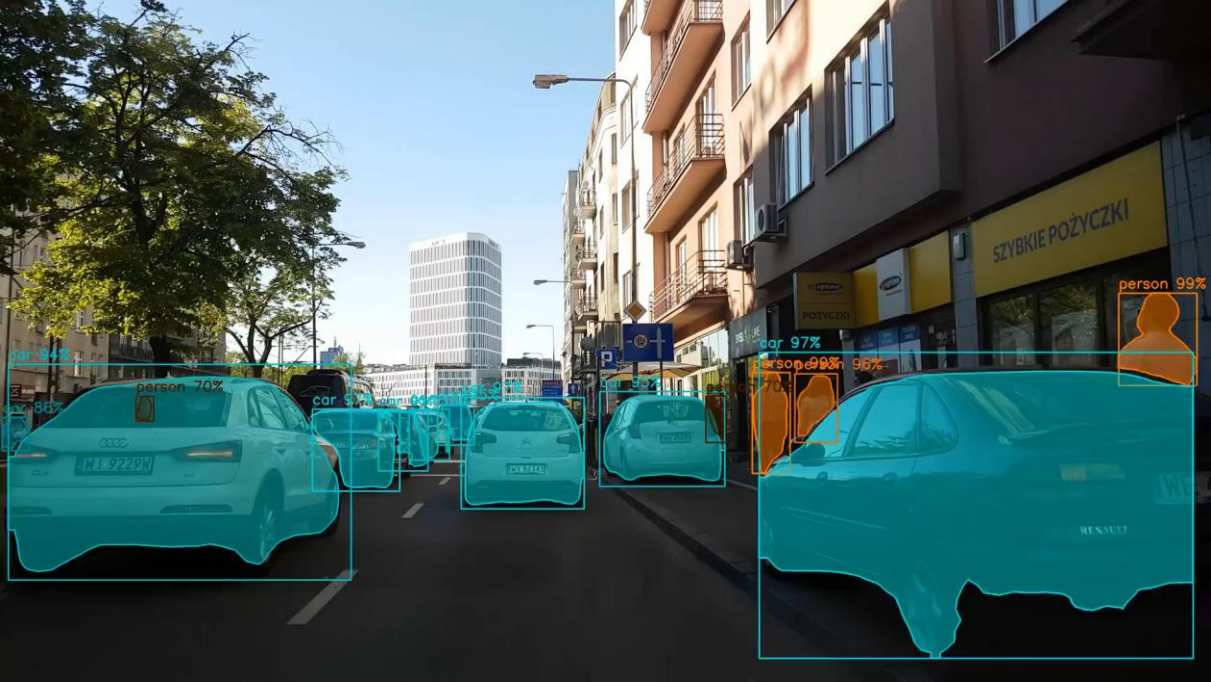

**Problem Setting:**

- **Input:** RGB Image or laser range scan
- **Output:** Set of 2D/3D bounding boxes with category label and confidence
- Note: Number of objects and object size not known a priori!

# 3D Object Detection

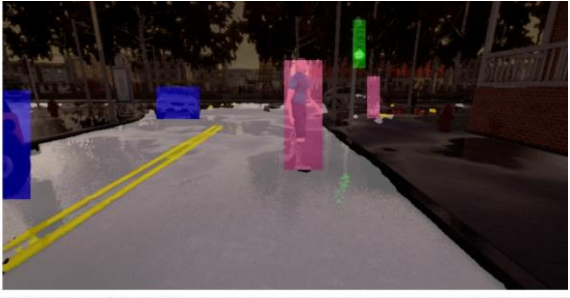

- **Input:** RGB Image or laser range scan
- **Output:** Set of 2D/3D bounding boxes with category label and confidence
- Note: Number of objects and object size not known a priori!


car 1.000
car 0.998
car 0.812
car 0.976
car 0.999
car 0.99
car 0.995
car 1.000
car 0.903
BADGLEY
MISCHKA


SZYBKIE POŻYCZKI
POŻYCZKI
person 99%
car 97%
person 96%
person 70%
RENAULT

# Visual Abstractions – What are most relevant segmentation classes for learning a driving policy?

Trained with 6400 finely annotated images and 14 classes
**Annotation time ≈ 7500 hours, policy success rate = 50%**



Trained with 1600 coarsely annotated images and 6 classes
**Annotation time ≈ 50 hours, policy success rate = 58%**

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

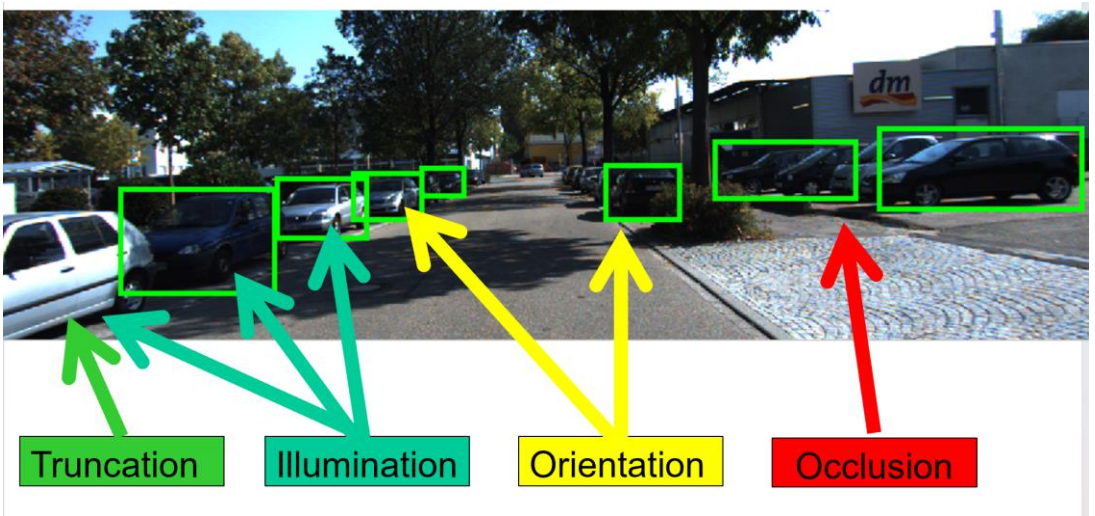
# Why is detection hard(er)?

Precise localization

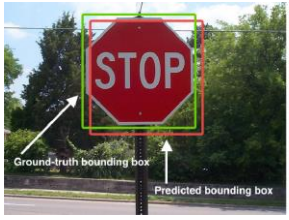
# Why is detection hard(er)?

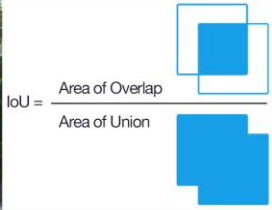
Small objects

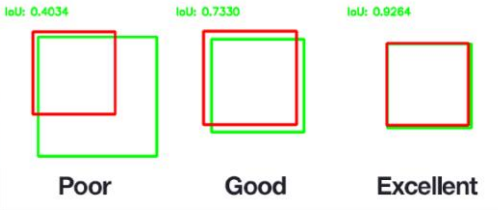
# Object Detection Challenges



# How to Measure Detection Performance?




**Measuring Bounding Box Alignment wrt. Ground Truth:**

- IoU = Intersection over union (predicted bbox vs. true bbox)
- Detection considered successful if IoU > 0.5
- How to fairly measure detection performance in case of multiple objects? (Number of detections depends on detector threshold and is detector specific!)

# Matching detections to ground truth

- Match detection to most similar ground truth
  - highest IoU
- If IoU > 50%, mark as correct
- If multiple detections map to same ground truth, mark only one as correct
- **Precision** = #correct detections / total detections
- **Recall** = #ground truth with matched detections / total ground truth

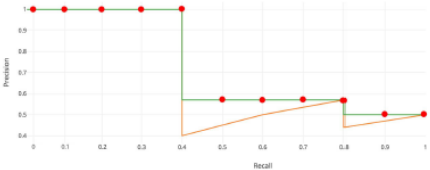
# Tradeoff between precision and recall

- ML usually gives scores or probabilities, so threshold
- Too low threshold → too many detections → low precision, high recall
- Too high threshold → too few detections → high precision, low recall
- Right tradeoff depends on application
  - Detecting cancer cells in tissue: need high recall
  - Detecting edible mushrooms in forest: need high precision

# How to Measure Detection Performance?

**Average Precision Metric:**

1. Run detector, varying det. threshold
2. Assign detections to closest object
3. Count TP, FP, FN
4. Compute **Average Precision (AP)**




**True Positives TP:** Number of objects correctly detected (IoU>0.5)

**False Negatives FN:** Number of objects not detected (IoU<0.5)

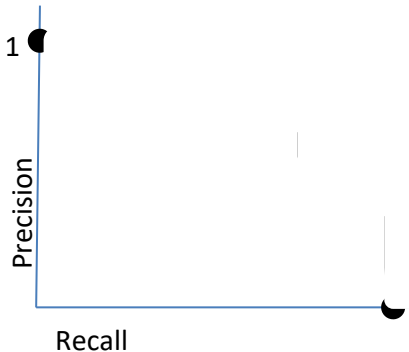
**False Positives FP:** Wrong detections

$$\text{Precision } P = \frac{TP}{TP+FP}$$

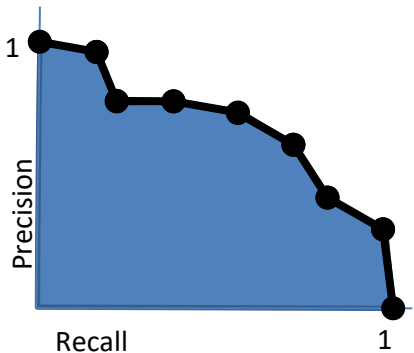
$$\text{Recall } R = \frac{TP}{TP+FN}$$

$$\text{Avg. Prec. } AP = \frac{1}{11} \sum_{R \in \{0,\ldots,1\}} \max_{R' \geq R} P(R')$$

# Average precision



# Average precision



https://www.cvlibs.net/datasets/kitti/

# Object Detection and Orientation Estimation Evaluation

## Cars

| | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 1 | VoCo | | | **97.11 %** | 98.25 % | **94.46 %** | 0.1 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| 2 | VirConv-S | | | 96.46 % | 96.99 % | 93.74 % | 0.09 s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| 3 | GraR-Vol | | code | 96.29 % | 96.81 % | 91.06 % | 0.07 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| | H. Yang, Z. Liu, X. Wu, W. Wang, W. Qian, X. He and D. Cai: Graph R-CNN: Towards Accurate 3D Object Detection with Semantic-Decorated Local Graph. ECCV 2022. | | | | | | | | |
| 4 | GraR-Po | | code | 96.09 % | 96.83 % | 90.99 % | 0.06 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| | H. Yang, Z. Liu, X. Wu, W. Wang, W. Qian, X. He and D. Cai: Graph R-CNN: Towards Accurate 3D Object Detection with Semantic-Decorated Local Graph. ECCV 2022. | | | | | | | | |
| 5 | NIV-SSD | | | 96.06 % | 96.89 % | 88.63 % | 0.03 s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| 6 | SFD | | code | 96.05 % | **98.95 %** | 90.96 % | 0.1 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| | X. Wu, L. Peng, H. Yang, L. Xie, C. Huang, C. Deng, H. Liu and D. Cai: Sparse Fuse Dense: Towards High Quality 3D Detection with Depth Completion. CVPR 2022. | | | | | | | | |
| 7 | VPFNet | | code | 96.04 % | 96.63 % | 90.99 % | 0.06 s | 2 cores @ 2.5 Ghz (Python) | ☐ |
| | H. Zhu, J. Deng, Y. Zhang, J. Ji, Q. Mao, H. Li and Y. Zhang: VPFNet: Improving 3D Object Detection with Virtual Point based LiDAR and Stereo Data Fusion. IEEE Transactions on Multimedia 2022. | | | | | | | | |
| 8 | VirConv-T | | | 96.01 % | 98.64 % | 93.12 % | 0.09 s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| 9 | CASDC | | | 95.97 % | 98.64 % | 92.99 % | 0.1 s | 1 core @ 2.5 Ghz (Python) | ☐ |
| 10 | TED | | code | 95.96 % | 96.63 % | 93.24 % | 0.1 s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| | H. Wu, C. Wen, W. Li, R. Yang and C. Wang: Transformation-Equivariant 3D Object Detection for Autonomous Driving. AAAI 2023. | | | | | | | | |
| 11 | RDIoU | | code | 95.95 % | 98.77 % | 90.90 % | 0.03 s | 1 core @ 2.5 Ghz (Python + C/C++) | ☐ |
| | H. Sheng, S. Cai, N. Zhao, B. Deng, J. Huang, X. Hua, M. Zhao and G. Lee: Rethinking IoU-based Optimization for Single- stage 3D Object Detection. ECCV 2022. | | | | | | | | |
| 12 | ACF-Net | | | 95.95 % | 96.64 % | 93.17 % | n/a s | 1 core @ 2.5 Ghz (C/C++) | ☐ |
| 13 | CLOCs | | code | 95.93 % | 96.77 % | 90.93 % | 0.1 s | 1 core @ 2.5 Ghz (Python) | ☐ |
| | S. Pang, D. Morris and H. Radha: CLOCs: Camera-LiDAR Object Candidates Fusion for 3D Object Detection . 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) 2020. | | | | | | | | |

# Good old days

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| OC-DPM | | | 64.42 % | 73.50 % | 52.40 % | 10 s | 8 cores @ 2.5 Ghz (Matlab) |

ik, M. Stark, P. Gehler and B. Schiele: Occlusion Patterns for Object Class Detection. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2013.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| LSVM-MDPM-sv | | | 55.77 % | 67.27 % | 43.59 % | 10 s | 4 cores @ 3.0 Ghz (C/C++) |

ger, C. Wojek and R. Urtasun: Joint 3D Estimation of Objects and Scene Layout. NIPS 2011.

enszwalb, R. Girshick, D. McAllester and D. Ramanan: Object Detection with Discriminatively Trained Part-Based Models. PAMI 2010.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| DPM-C8B1 | | | 50.32 % | 59.51 % | 39.22 % | 15 s | 4 cores @ 2.5 Ghz (Matlab + C/C++) |

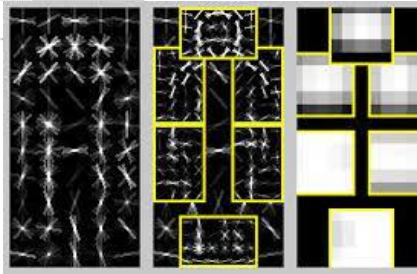
nous submission

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| AOG | | | 36.87 % | 44.41 % | 30.29 % | 3 s | 4 cores @ 2.5 Ghz (Matlab) |

nous submission

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| SVM-Res | | | 30.38 % | 35.02 % | 24.87 % | 10 s | 4 cores @ 2.5 Ghz (Matlab) |

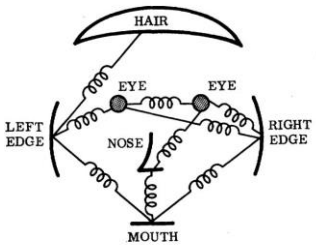
nous submission

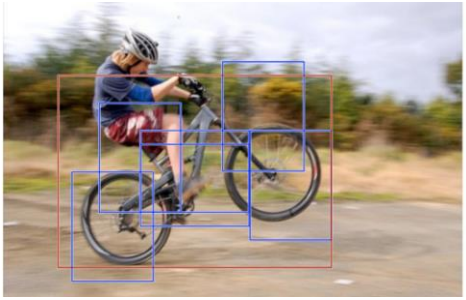


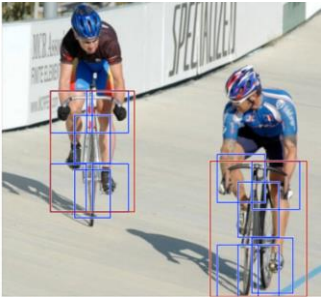
# Part Based Models

**Part-based Models:**

- Idea: Model object based on its parts, model distribution of part configurations
- Allows for even more invariance (non-rigid deformations etc.)
- However: slower inference and not much gain wrt. multi-view HoG models

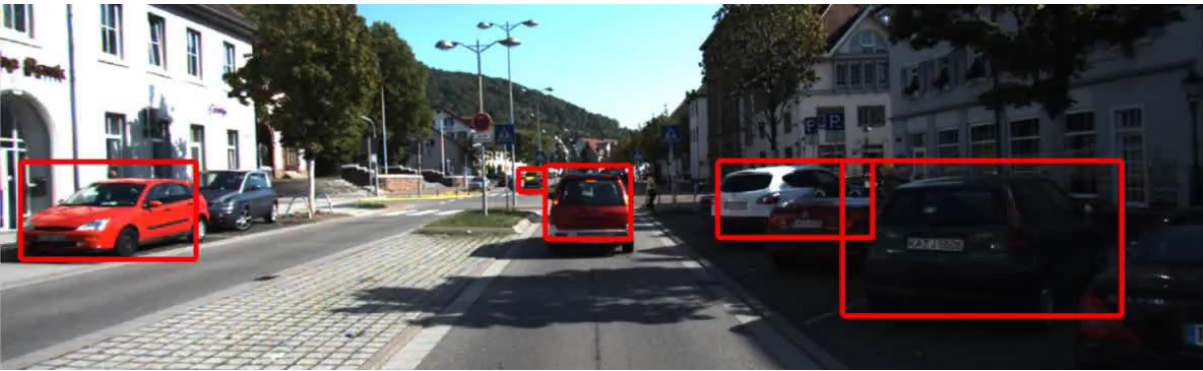




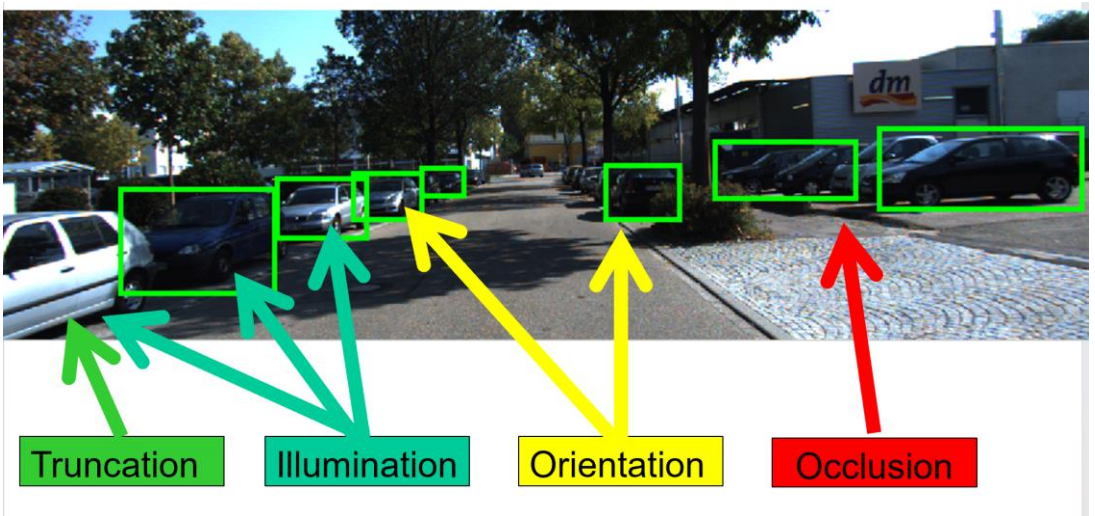
Object Detection with Discriminatively Trained Part Based Models. Felzenszwalb, Girshick, McAllester and Ramanan. PAMI, 2010.

# Results on KITTI

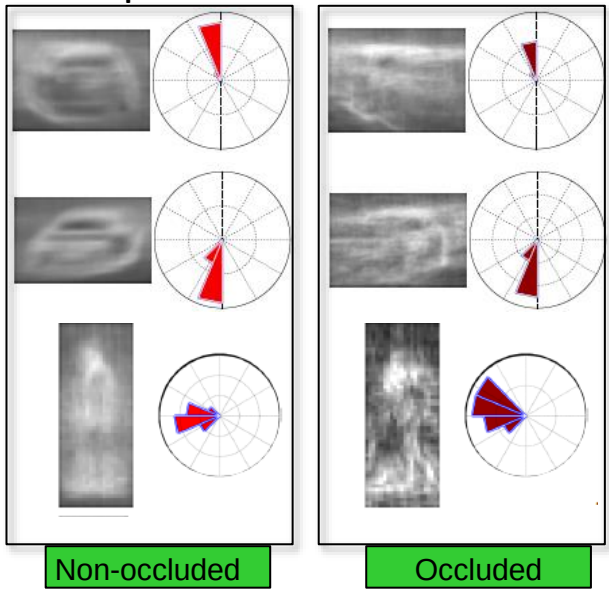


Object Detection with Discriminatively Trained Part Based Models. Felzenszwalb, Girshick, McAllester and Ramanan. PAMI, 2010.

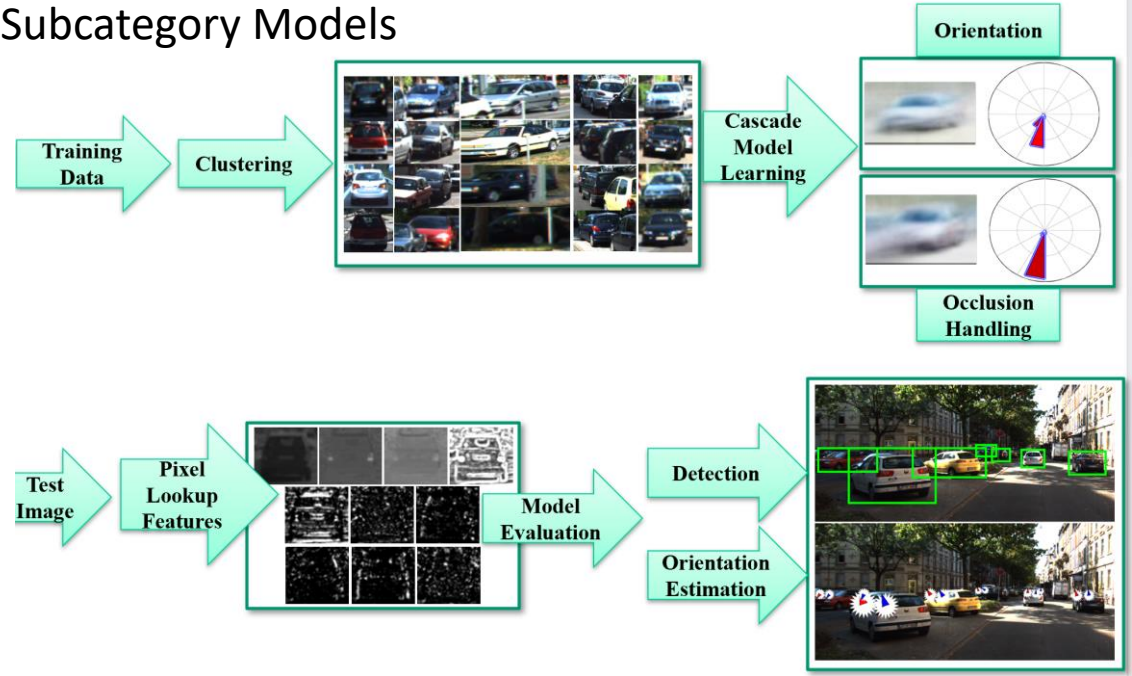
# Object Detection Challenges



# Key Idea: Learn Multiple Models



# Subcategory Models



# Object Detection and Orientation Estimation Evaluation

## Cars

| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 1 | SubCat | | | 64.94 % | 80.92 % | 50.03 % | 0.3 s | 6 cores @ 2.5 Ghz (Matlab + C/C++) | |

E. Ohn-Bar and M. Trivedi: Learning to Detect Objects at Multiple Orientations and Occlusion Levels. Under submission 2014.

| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 2 | OC-DPM | | | 64.42 % | 73.50 % | 52.40 % | 10 s | 8 cores @ 2.5 Ghz (Matlab) | |

B. Pepik, M. Stark, P. Gehler and B. Schiele: Occlusion Patterns for Object Class Detection. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2013.

| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 3 | LSVM-MDPM-sv | | | 55.77 % | 67.27 % | 43.59 % | 10 s | 4 cores @ 3.0 Ghz (C/C++) | |

A. Geiger, C. Wojek and R. Urtasun: Joint 3D Estimation of Objects and Scene Layout. NIPS 2011.

P. Felzenszwalb, R. Girshick, D. McAllester and D. Ramanan: Object Detection with Discriminatively Trained Part-Based Models. PAMI 2010.

| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 4 | DPM-C8B1 | | | 50.32 % | 59.51 % | 39.22 % | 15 s | 4 cores @ 2.5 Ghz (Matlab + C/C++) | |

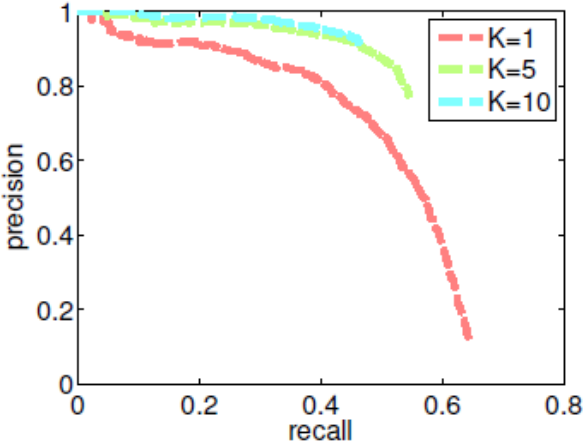
Anonymous submission

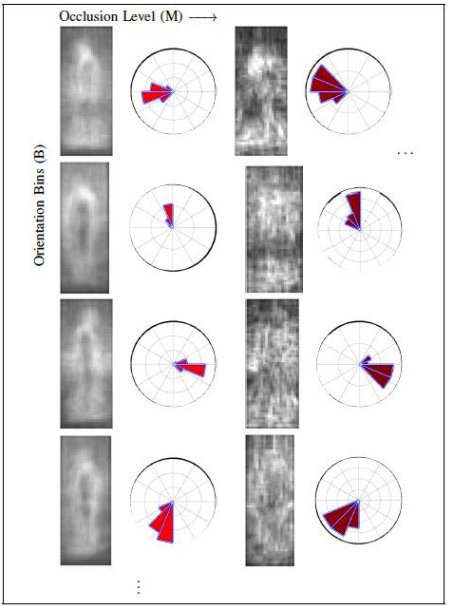
| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 5 | AOG | | | 36.87 % | 44.41 % | 30.29 % | 3 s | 4 cores @ 2.5 Ghz (Matlab) | |

Anonymous submission

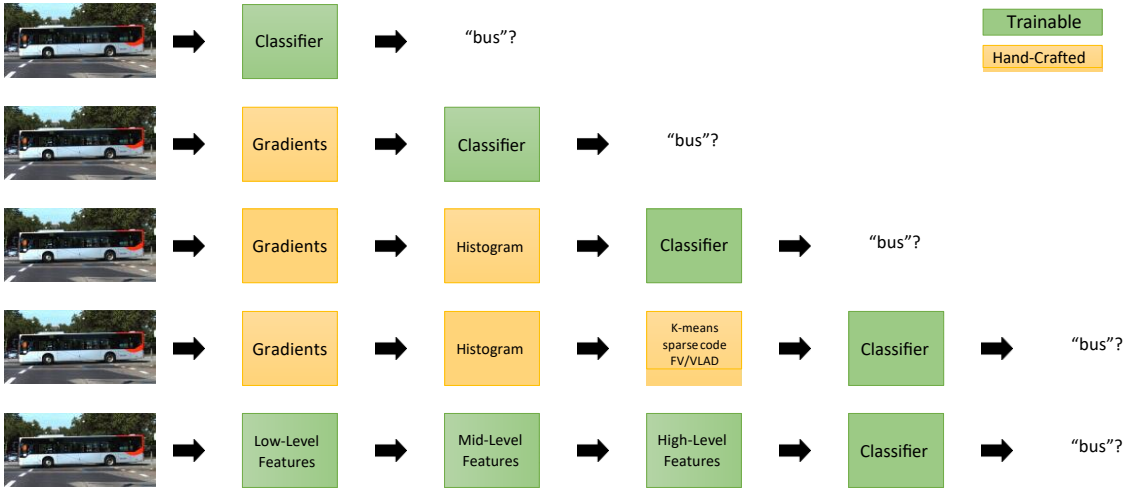
| Rank | Method | Setting | Code | Moderate | Easy | Hard | Runtime | Environment | Compare |
|---|---|---|---|---|---|---|---|---|---|
| 6 | SVM-Res | | | 30.38 % | 35.02 % | 24.87 % | 10 s | 4 cores @ 2.5 Ghz (Matlab) | |

Anonymous submission


precision
recall
K=1
K=5
K=10
0
0.2
0.4
0.6
0.8
1

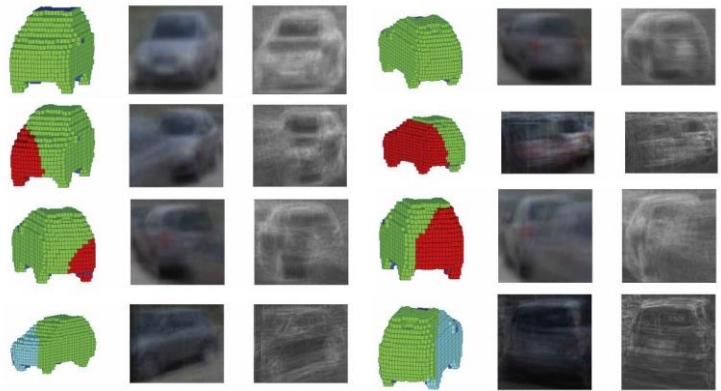

Occlusion Level (M) ⟶
Orientation Bins (B)

# Hand-crafted Representations vs. Learned Representations



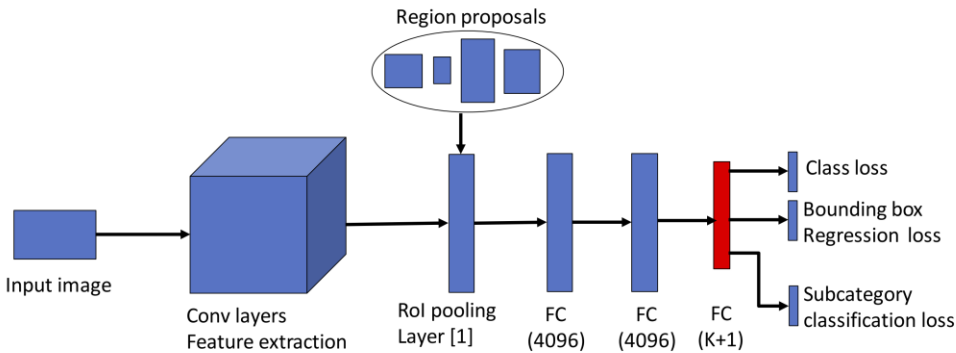
Data-Driven 3D Voxel Patterns for Object Category Recognition, Xiang et al., CVPR 2015

Cluster objects with similar 3D pose, occlusion and truncation.



# Subcategory-aware Convolutional Neural Networks for Object Proposals and Detection, WACV 2017

## Subcategory-aware Detection Network




[1] R. Girshick. Fast R-CNN. ICCV, 2015.

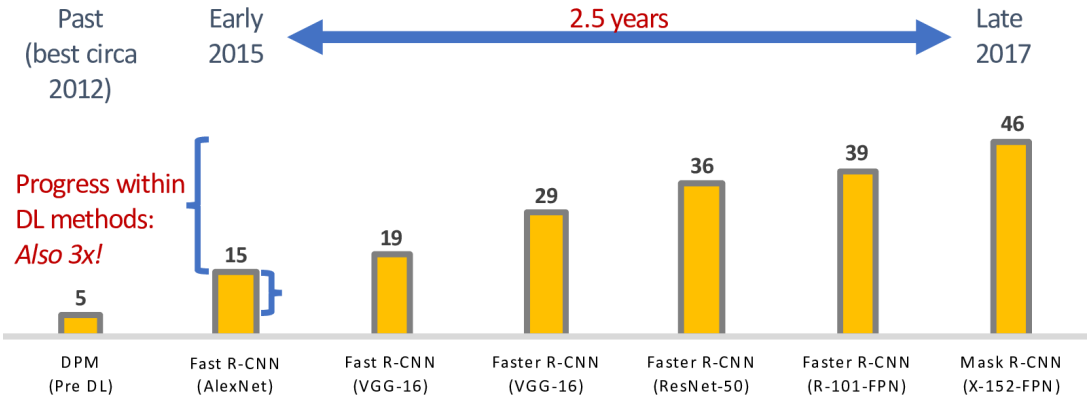
# Car Detection and Orientation Estimation on KITTI

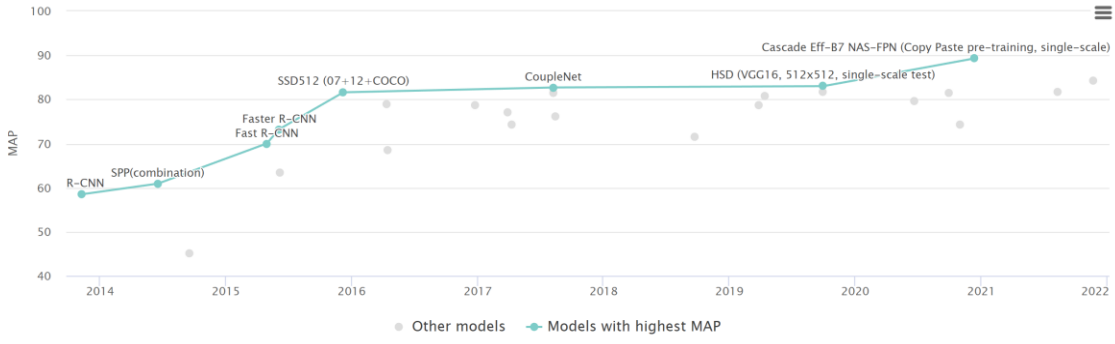
| | Object Detection (AP) | | | Object Detection and Orientation estimation (AOS) | | |
|---|---|---|---|---|---|---|
| **Method** | **Easy** | **Moderate** | **Hard** | **Easy** | **Moderate** | **Hard** |
| ACF [1] | 55.89 | 54.77 | 42.98 | N/A | N/A | N/A |
| DPM-VOC+VP [2] | 74.95 | 64.71 | 48.76 | 72.28 | 61.84 | 46.54 |
| OC-DPM [3] | 74.94 | 65.95 | 53.86 | 73.50 | 64.42 | 52.40 |
| SubCat [4] | 84.14 | 75.46 | 59.71 | 83.41 | 74.42 | 58.83 |
| Regionlets [5] | 84.75 | 76.45 | 59.70 | N/A | N/A | N/A |
| 3DVP [6] | 84.81 | 73.02 | 63.22 | 84.31 | 71.99 | 62.11 |
| 3DOP [7] | **93.04** | 88.64 | 79.10 | **91.44** | 86.10 | 76.52 |
| Mono3D [8] | 92.33 | 88.66 | 78.96 | 91.01 | 86.62 | 76.84 |
| SDP+RPN [9] | 90.14 | 88.85 | 78.38 | N/A | N/A | N/A |
| MS-CNN [10] | 90.03 | 89.02 | 76.11 | N/A | N/A | N/A |
| **Ours** SubCNN | 90.81 | **89.04** | **79.27** | 90.67 | **88.62** | **78.68** |


[1] P. Dolla´r, R. Appel, S. Belongie, and P. Perona. Fast feature pyramids for object detection. TPAMI, 2014.
[2] B. Pepik, M. Stark, P. Gehler, and B. Schiele. Multi-view and 3d deformable part models. TPAMI, 2015.
[3] B. Pepikj, M. Stark, P. Gehler, and B. Schiele. Occlusion patterns for object class detection. In CVPR, 2013.
[4] E. Ohn-Bar and M. M. Trivedi. Learning to detect vehicles by clustering appearance patterns. T-ITS, 2015.
[5] X. Wang, M. Yang, S. Zhu, and Y. Lin. Regionlets for generic object detection. In ICCV, 2013.
[6] Y. Xiang, W. Choi, Y. Lin, and S. Savarese. Data-driven 3d voxel patterns for object category recognition. In CVPR, 2015.
[7] X. Chen, K. Kundu, Y. Zhu, A. G. Berneshawi, H. Ma, S. Fidler, and R. Urtasun. 3d object proposals for accurate object class detection. In NIPS, 2015.
[8] X. Chen, K. Kundu, Z. Zhang, H. Ma, S. Fidler, R. Urtasun. Monocular 3D Object Detection for Autonomous Driving, in CVPR, 2016.
[9] F. Yang, W. Choi, and Y. Lin. Exploit all the layers: Fast and accurate cnn object detector with scale dependent pooling and cascaded rejection classifiers. In CVPR, 2016.
[10] Z. Cai, Q. Fan, R. Feris, and N. Vasconcelos. A unified multi-scale deep convolutional neural network for fast object detection. In ECCV, 2016.

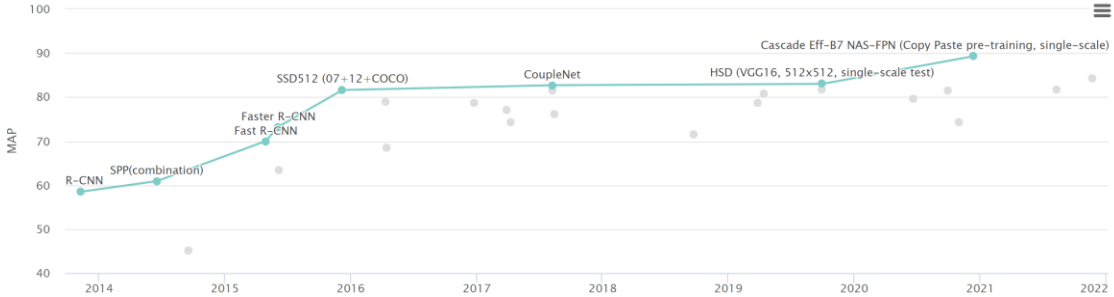

Detection: Rank 2
Pose : Rank 4

# Hand-crafted Representations vs. Learned Representations





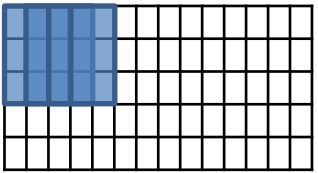

| | | | | | |
|---|---|---|---|---|---|
| 25 | **R-CNN** | 58.5% | Rich feature hierarchies for accurate object detection and semantic segmentation | | 2013 |
| 26 | **Deformable Parts Model** (DeepPyramid) | 45.2% | Deformable Part Models are Convolutional Neural Networks | | 2014 |



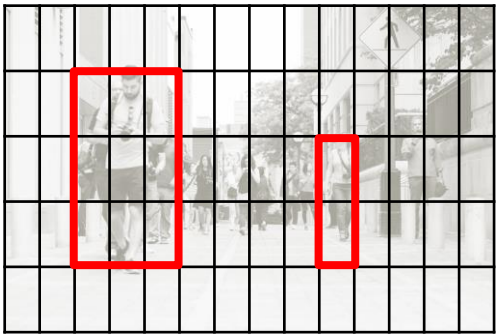

| | | | | | |
|---|---|---|---|---|---|
| 18 | **FRCN** | 74.2% | A-Fast-RCNN: Hard Positive Generation via Adversary for Object Detection | 2017 | |
| 19 | **Faster R-CNN** | 73.2% | Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks | 2015 | |
| 20 | **VGG-16 + KL Loss + var voting + soft-NMS** | 71.6% | Bounding Box Regression with Uncertainty for Accurate Object Detection | 2018 | |
| 21 | **Fast R-CNN** | 70.0% | Fast R-CNN | 2015 | |
| 22 | **subCNN** | 68.5% | Subcategory-aware Convolutional Neural Networks for Object Proposals and Detection | 2016 | |
| 23 | **YOLO** | 63.4% | You Only Look Once: Unified, Real-Time Object Detection | 2015 | YOLO |
| 24 | **SPP** (combination) | 60.9% | Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition | 2014 | |
| 25 | **R-CNN** | 58.5% | Rich feature hierarchies for accurate object detection and semantic segmentation | 2013 | |
| 26 | **Deformable Parts Model** (DeepPyramid) | 45.2% | Deformable Part Models are Convolutional Neural Networks | 2014 | |

# Idea 1: scanning window

- Fix size
  - Can take a few different sizes
- Fixed stride
- Convolution with a filter
  - Classic: compute HOG/CNN features over entire image



# Dealing with scale



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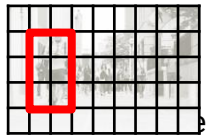
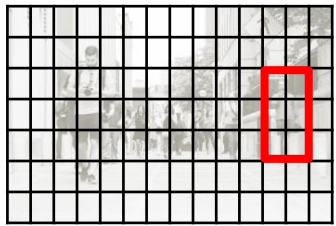


e window size, but run on *image pyramid*

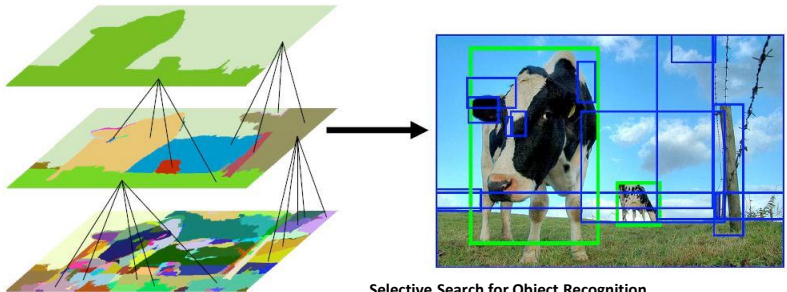


# Issues – Large Sampling Space

Run through every possible box and classify – over 10^10 for 300x500 images

# Idea 2: Object proposals

Use segmentation to produce ~5K candidates

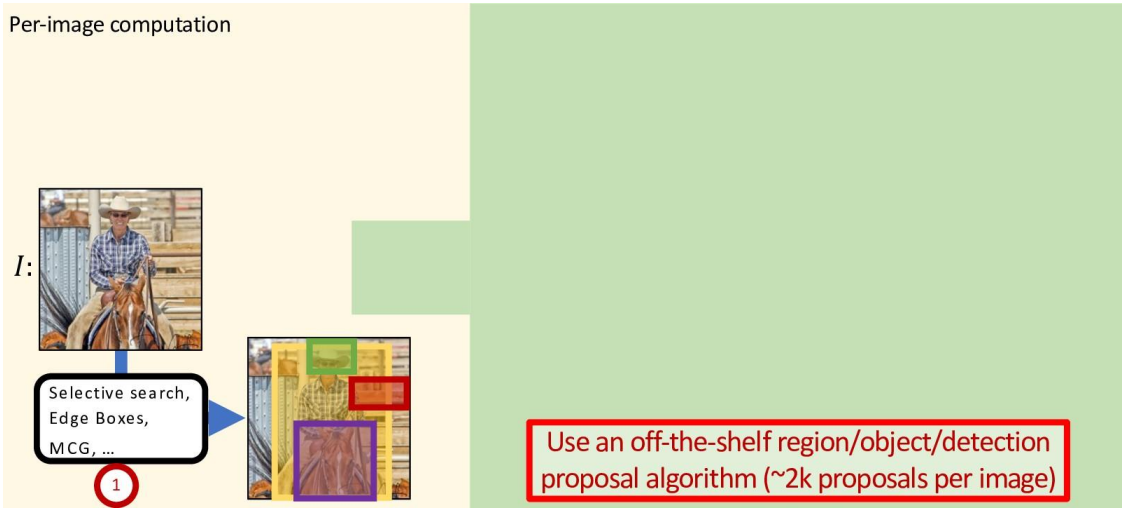


**Selective Search for Object Recognition**
J. R. R. Uijlings, K. E. A. van de Sande, T. Gevers, A. W. M. Smeulders
In International Journal of Computer Vision 2013.

# What do we do with proposals?

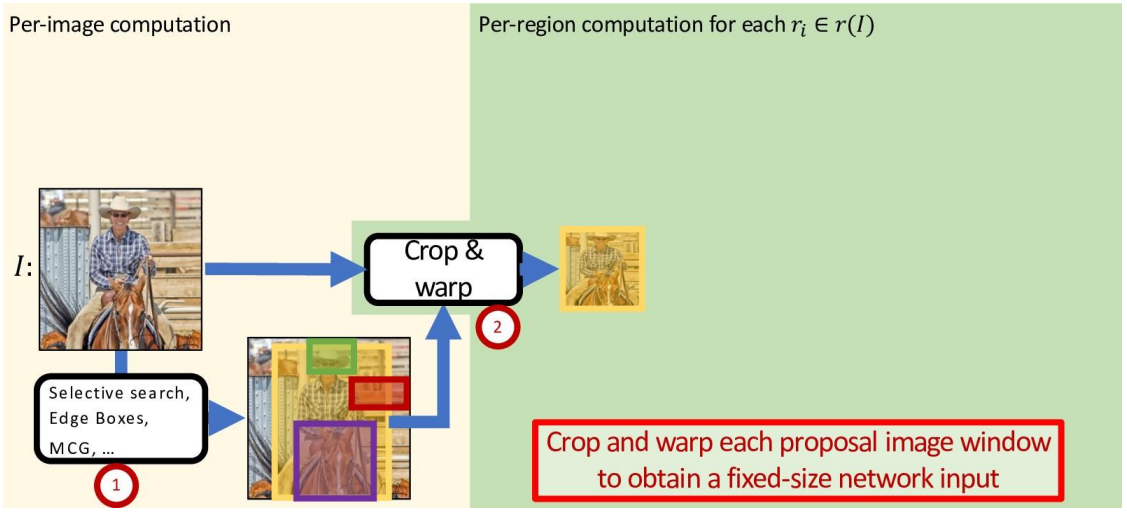
Each proposal is a group of pixels
Take tight fitting box and *classify it*
*Can leverage any image classification approach*

# R-CNN: Region-based Convolutional Neural Network




Girshick, Donahue, Darrell and Malik: Rich feature hierarchies for accurate object detection and semantic segmentation. CVPR, 2014.

# R-CNN: Region-based Convolutional Neural Network

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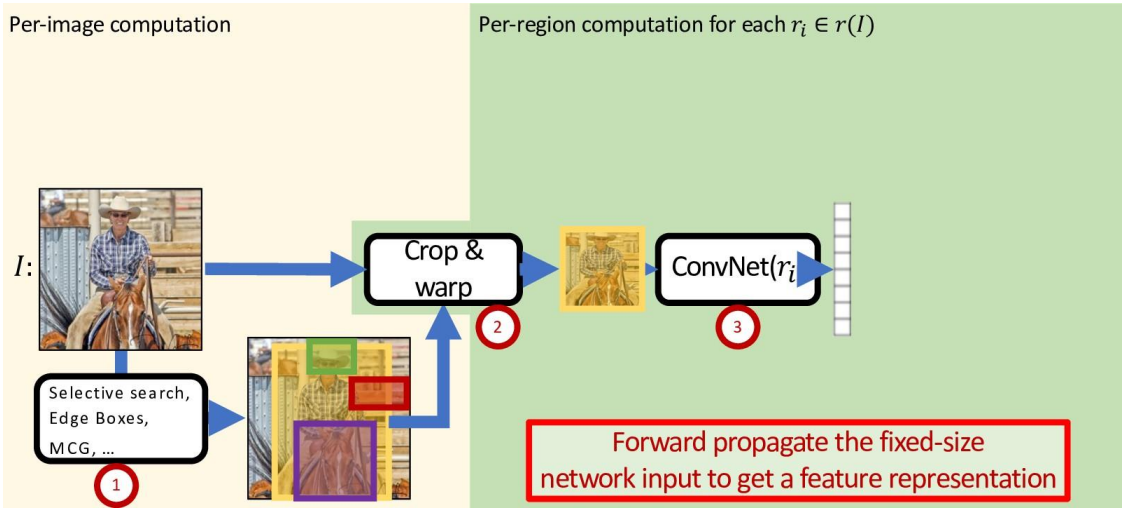


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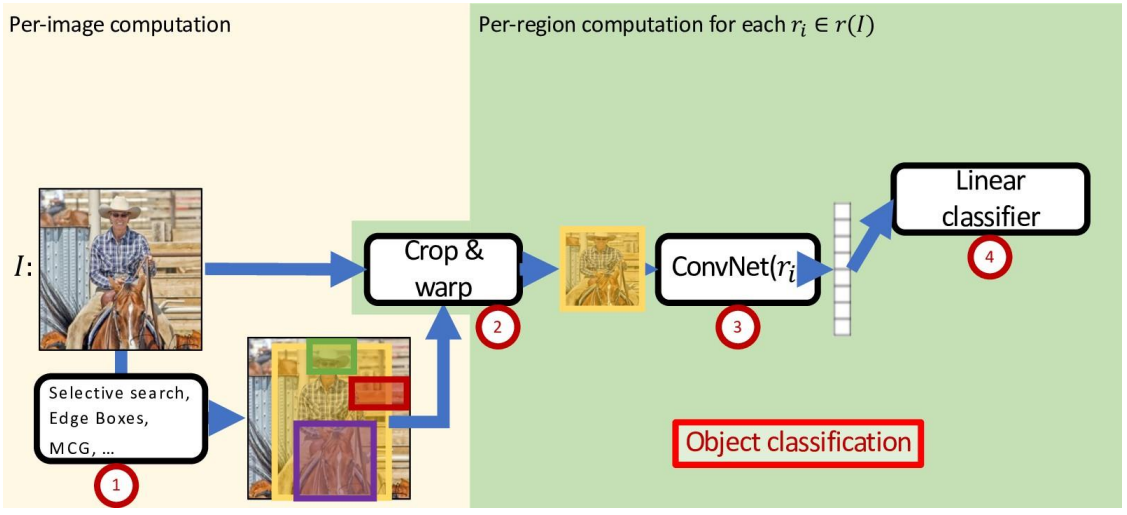


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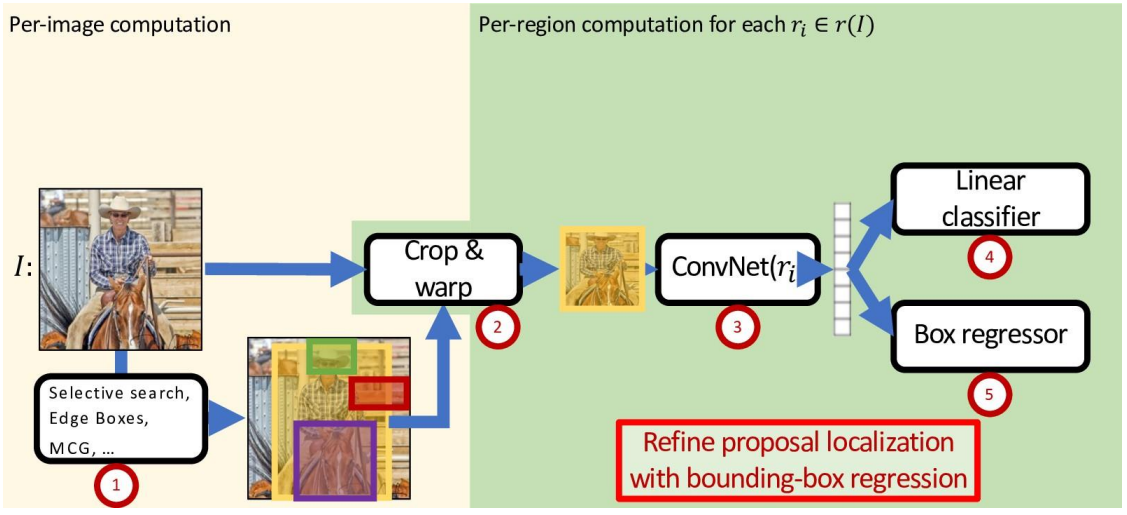



Girshick, Donahue, Darrell and Malik: Rich feature hierarchies for accurate object detection and semantic segmentation. CVPR, 2014.

# Generalized Framework

Per-image computation

$I$:

Per-region computation for each $r_i \in r(I)$

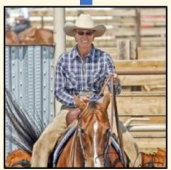
Input image
per-image operations | per-region operations

Girshick, Donahue, Darrell and Malik: Rich feature hierarchies for accurate object detection and semantic segmentation. CVPR, 2014.

# Generalized Framework

Per-image computation

$f_I = f(I)$



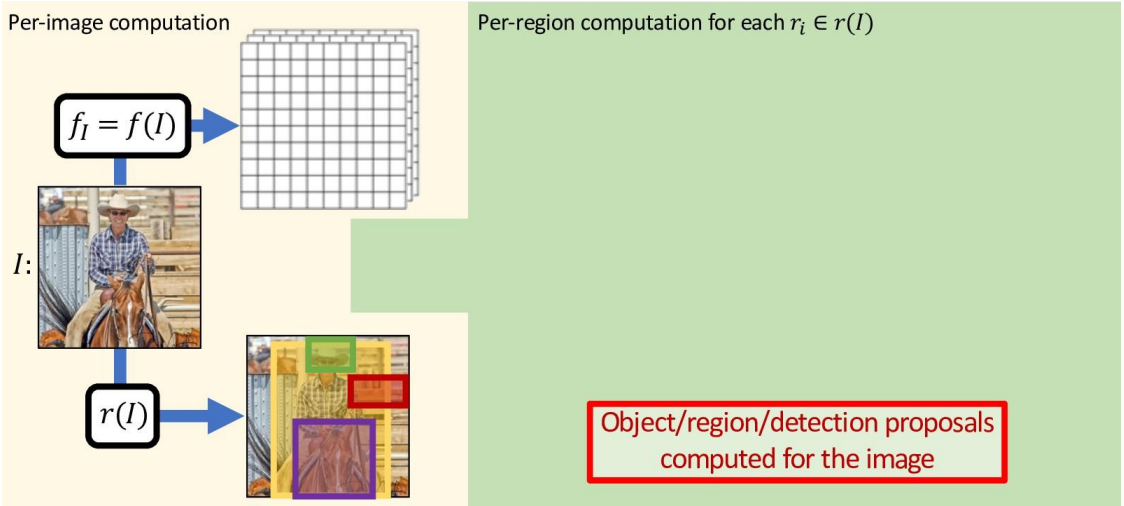
$I$:

Per-region computation for each $r_i \in r(I)$

Transformation of the input image into a featurized representation

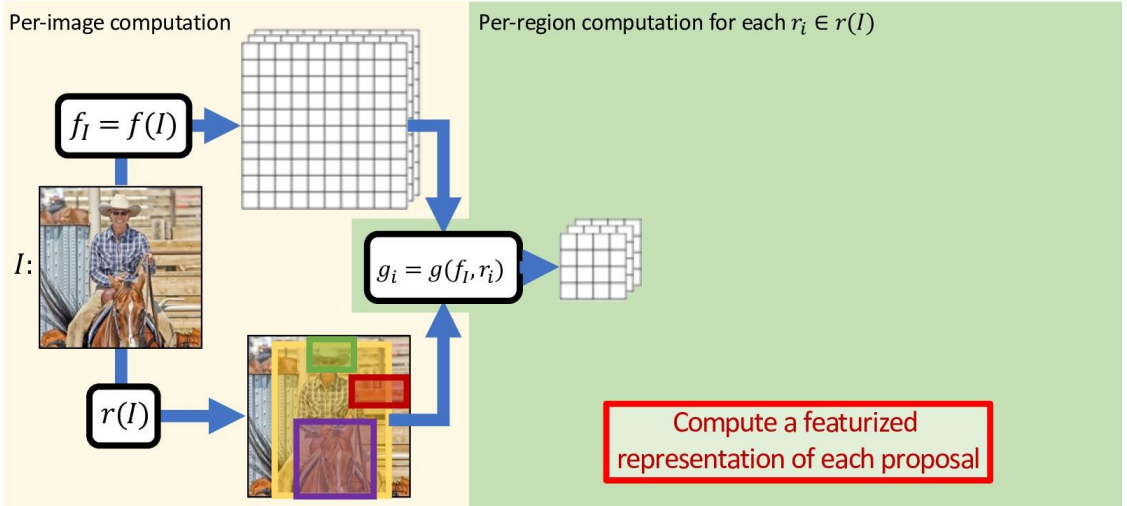
Girshick, Donahue, Darrell and Malik: Rich feature hierarchies for accurate object detection and semantic segmentation. CVPR, 2014.

# Generalized Framework




Girshick, Donahue, Darrell and Malik: Rich feature hierarchies for accurate object detection and semantic segmentation. CVPR, 2014.

# Generalized Framework

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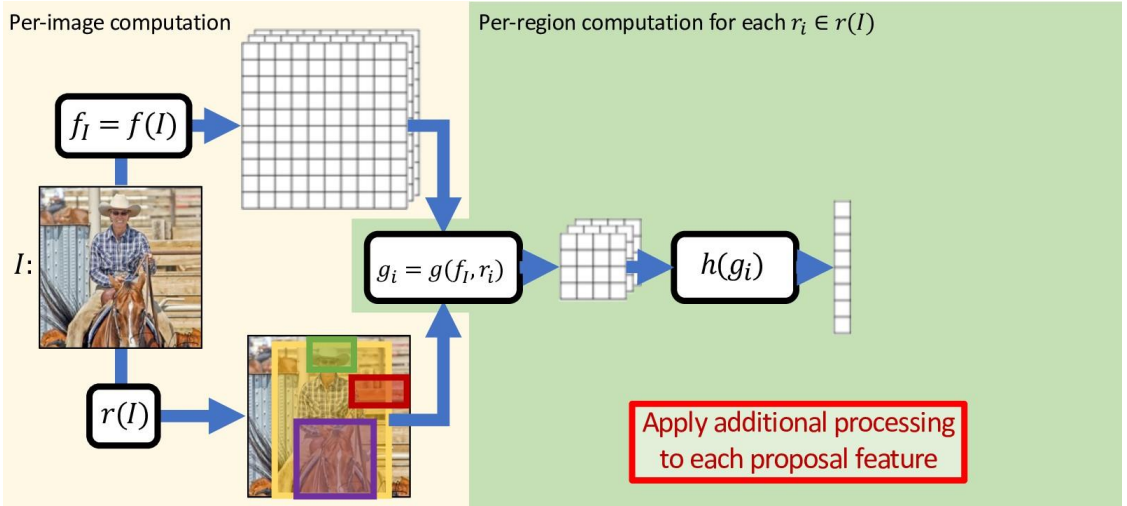


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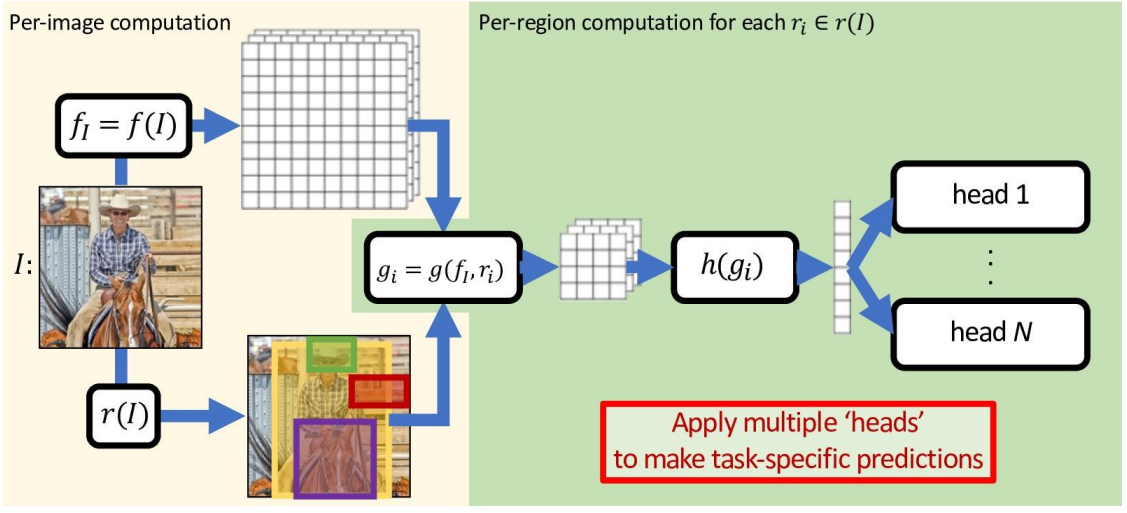


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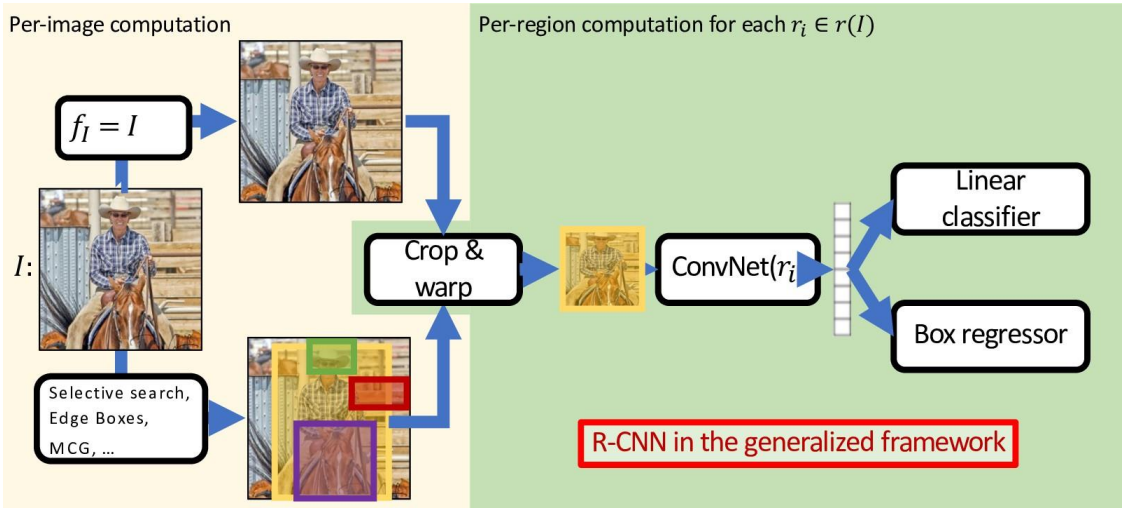
# R-CNN in Generalized Framework

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# R-CNN in Generalized Framework

What is the problem with R-CNN?

- Heavy per-region computation (e.g., 2000 full network evaluations)
- No computation/feature sharing
- Slow region proposal method adds to runtime
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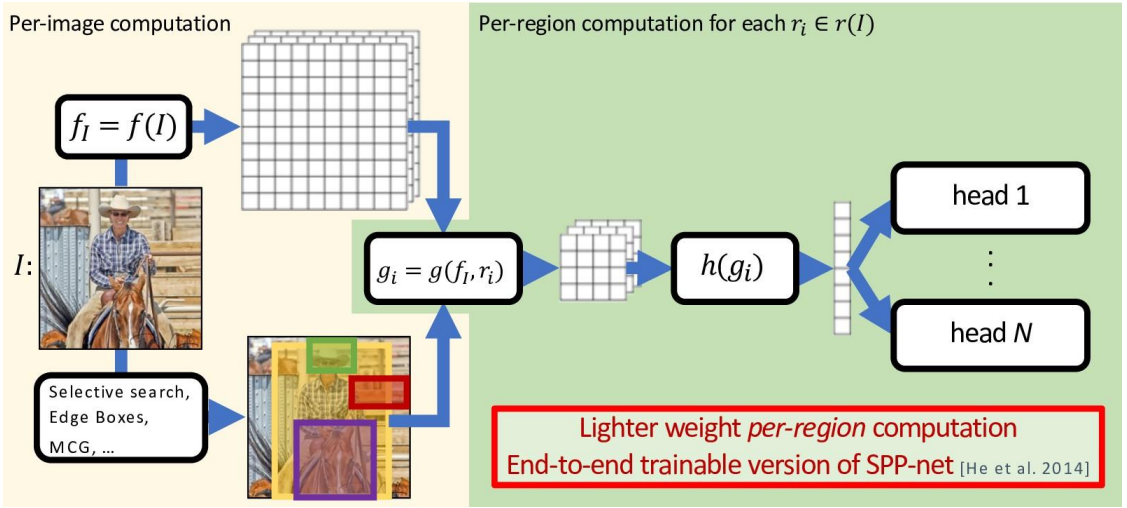
# Fast R-CNN




Girshick: Fast R-CNN. ICCV, 2015.

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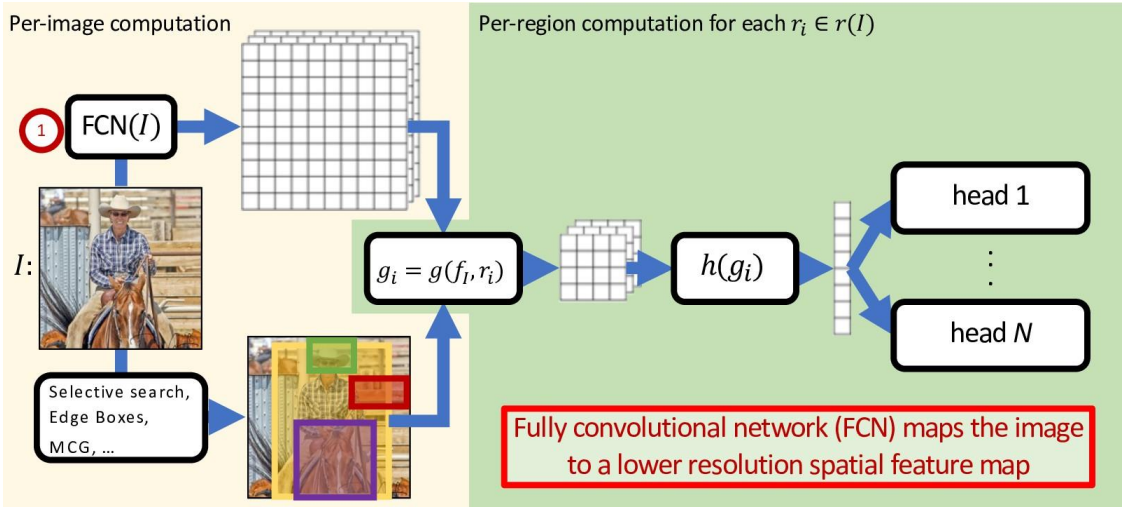


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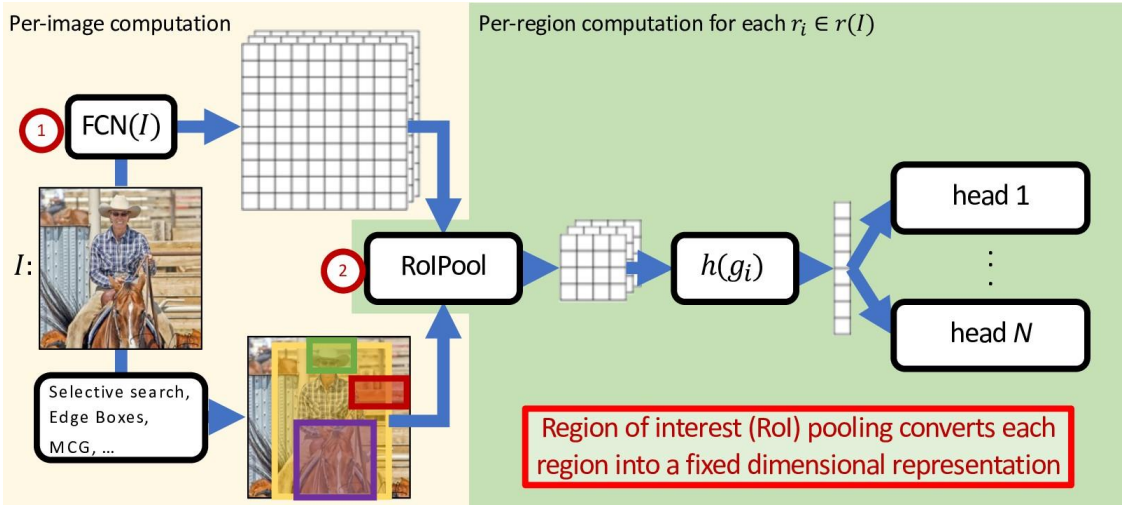


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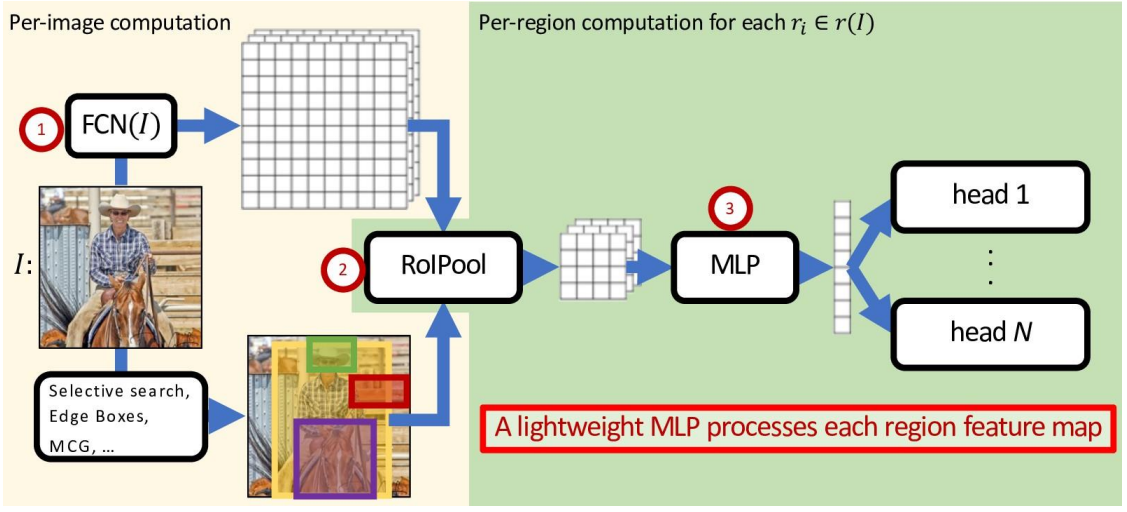


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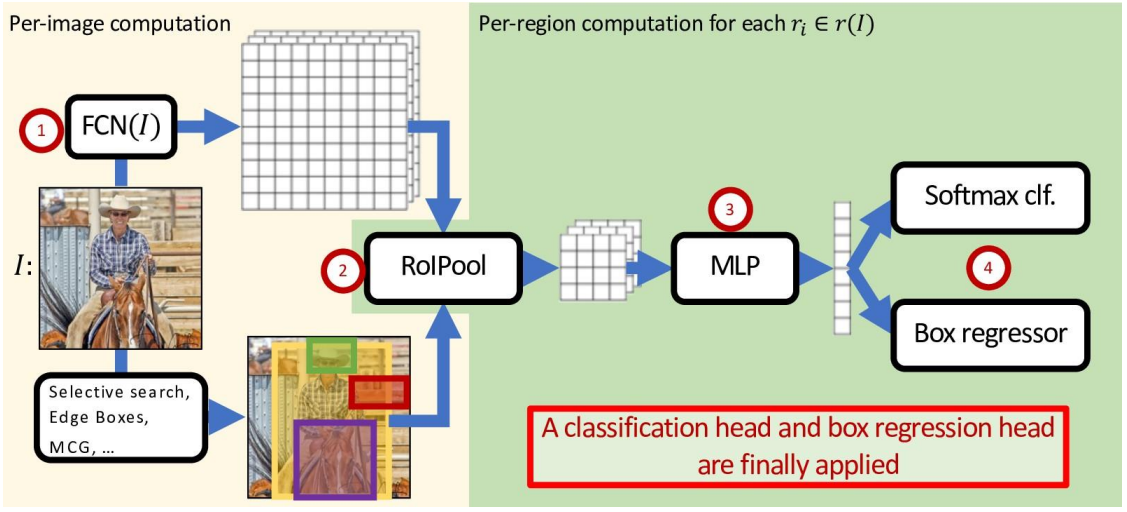


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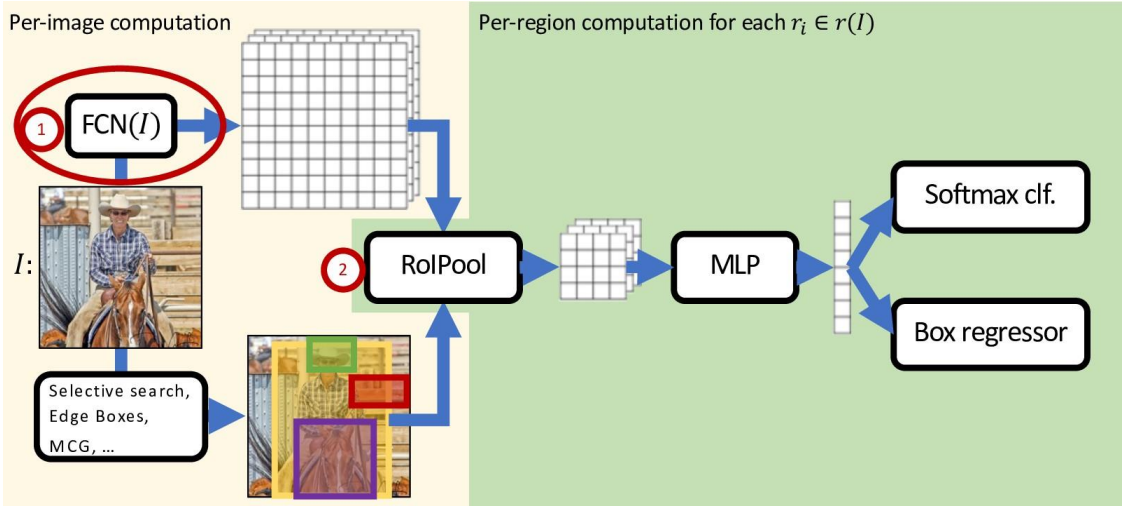
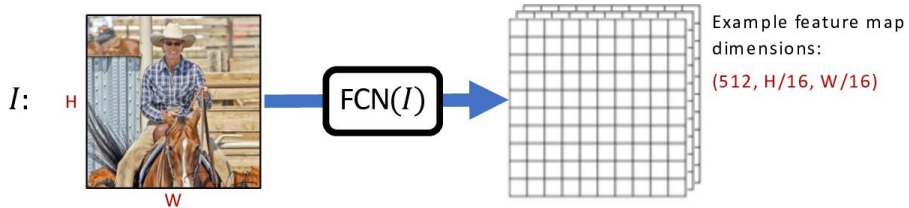



Girshick: Fast R-CNN. ICCV, 2015.

# Fast R-CNN

**Backbone:**

- Use any standard convolutional network as "backbone" architecture
  - E.g.: AlexNet, VGG, ResNet, Inception, ResNeXt, DenseNet, ...
- Remove global pooling ⇒ output spatial dims proportional to input spatial dims
- A good network exploits the strongest recognition backbone (features matter!)

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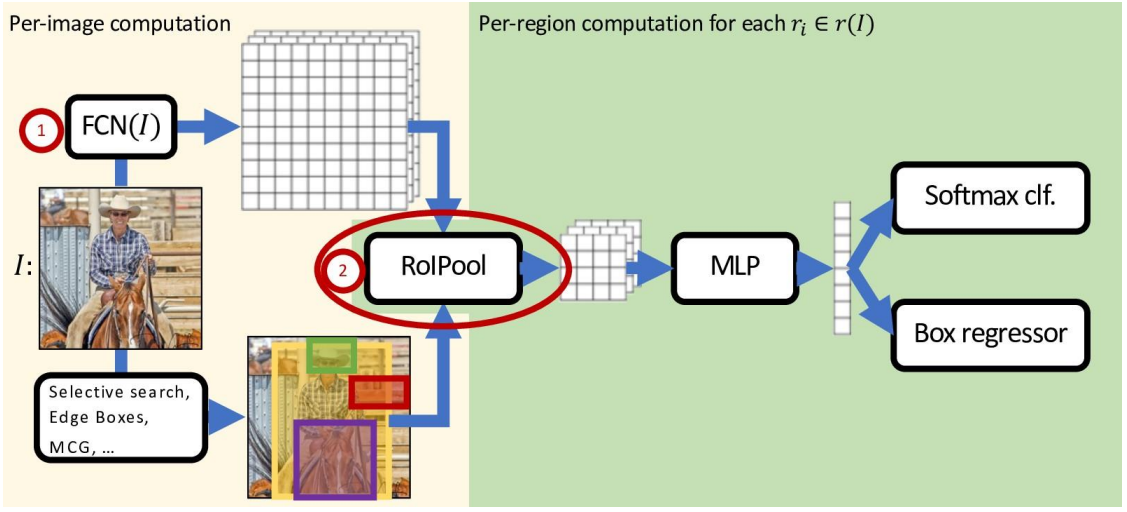


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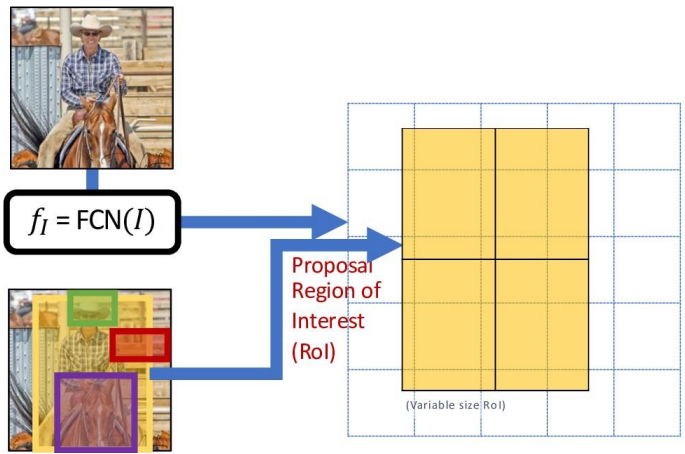
# Fast R-CNN

**Region-of-Interest (RoI) Pooling on each Proposal:**




Key innovation in SPP-net
[He et al. 2014]

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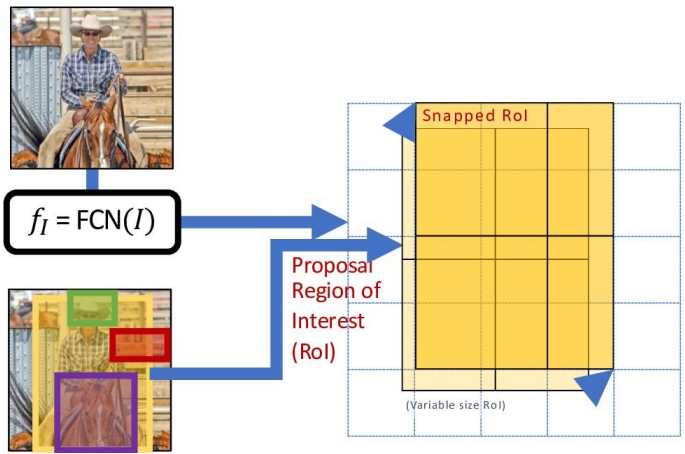


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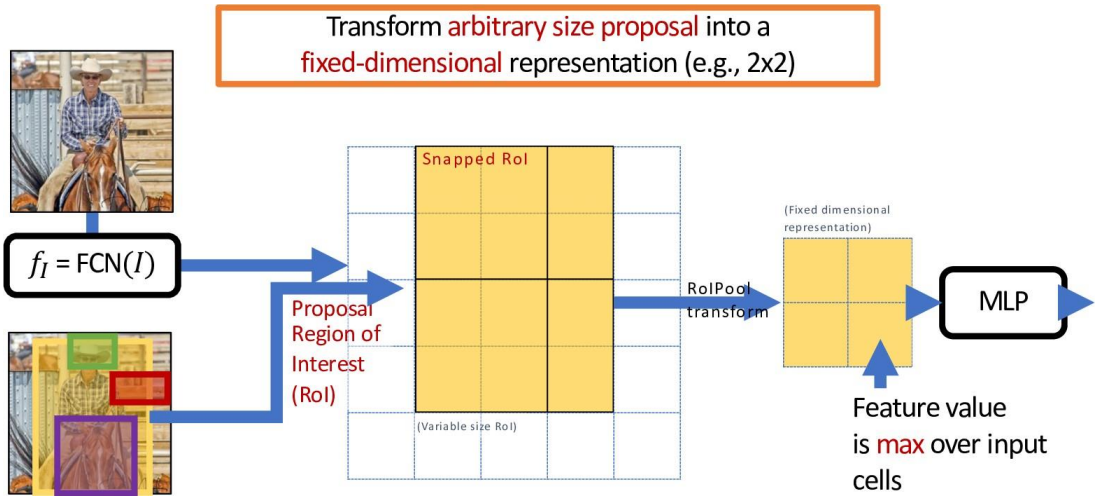


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# Fast R-CNN

What is the problem with Fast R-CNN?

- ~~Heavy per-region computation (e.g., 2000 full network evaluations)~~
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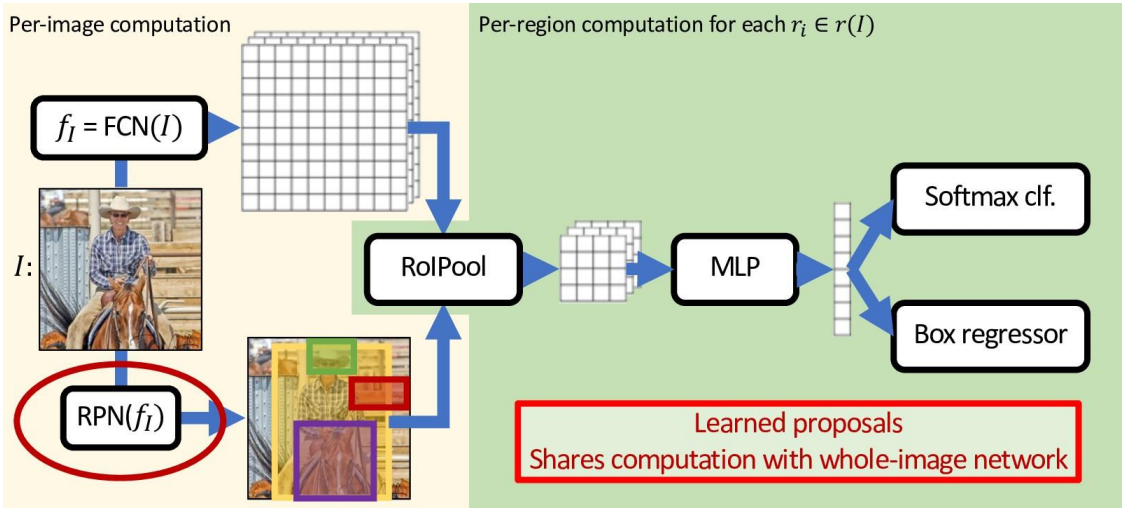
# Faster R-CNN




Ren, He, Girshick and Sun et al.: Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. NeurIPS, 2015.

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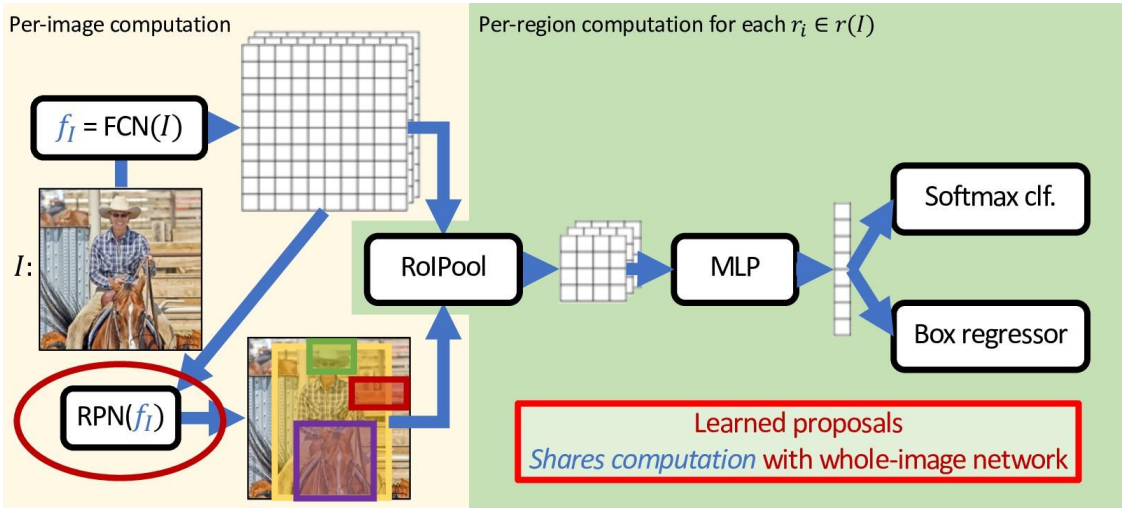


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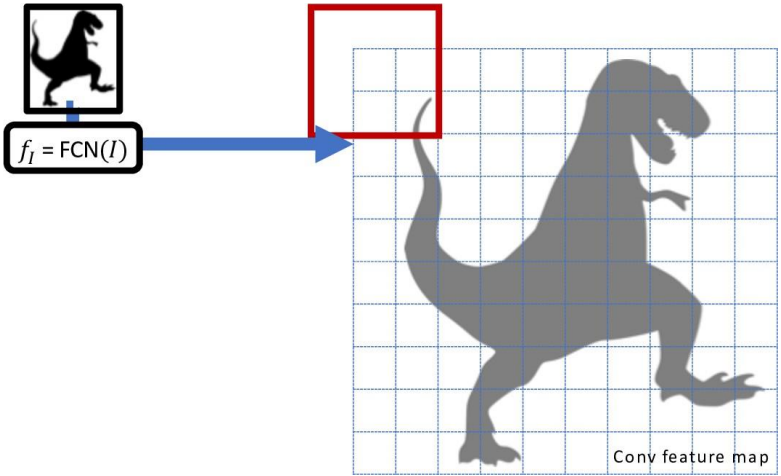
# Faster R-CNN: Region Proposal Network (RPN)

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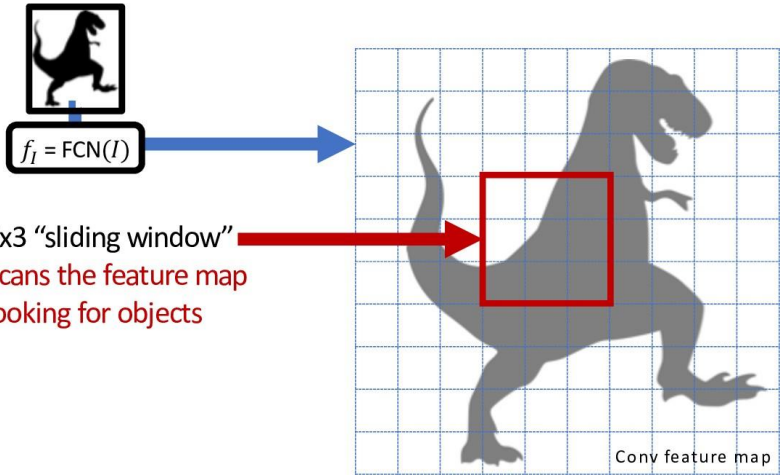


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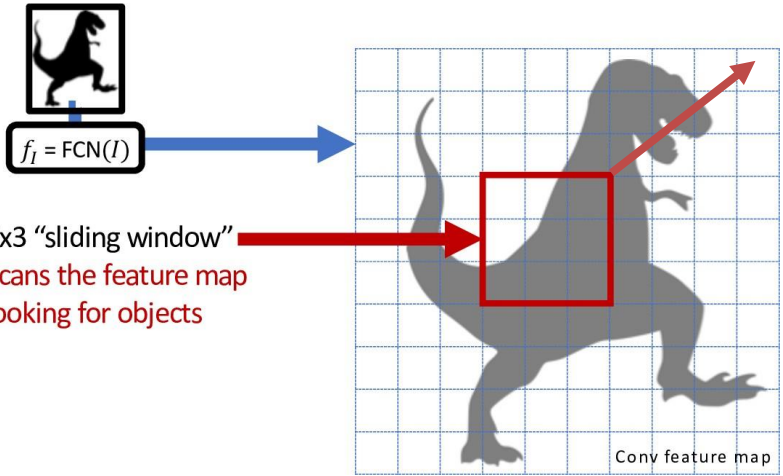
# Regression from Red Box to Full Object is Difficult!

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# Faster R-CNN: Region Proposal Network (RPN)

$f_I$ = FCN($I$)

Anchor box: predictions are w.r.t. this box, *not the 3x3 sliding window*

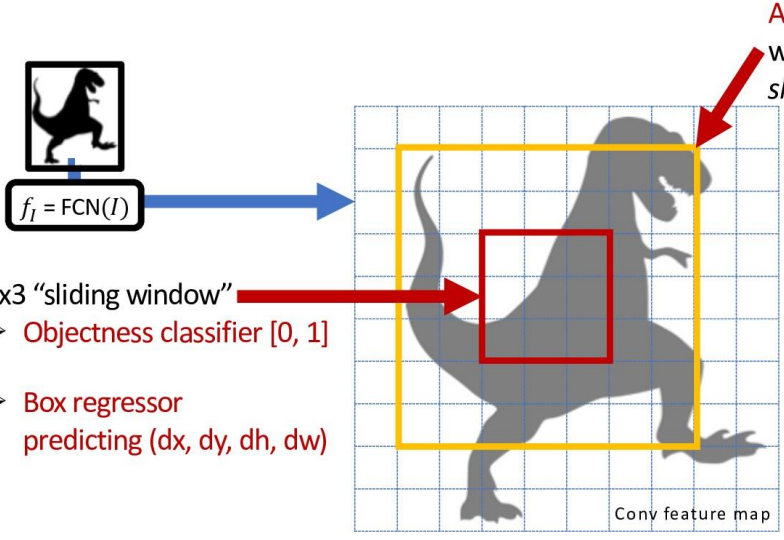
3x3 "sliding window"

Scans the feature map looking for objects

Conv feature map

Ren, He, Girshick and Sun et al.: Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. NeurIPS, 2015.

# Faster R-CNN: Region Proposal Network (RPN)

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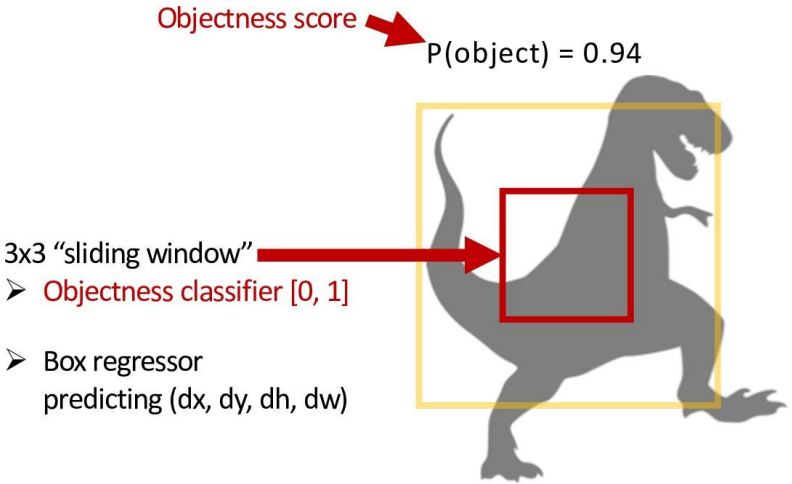


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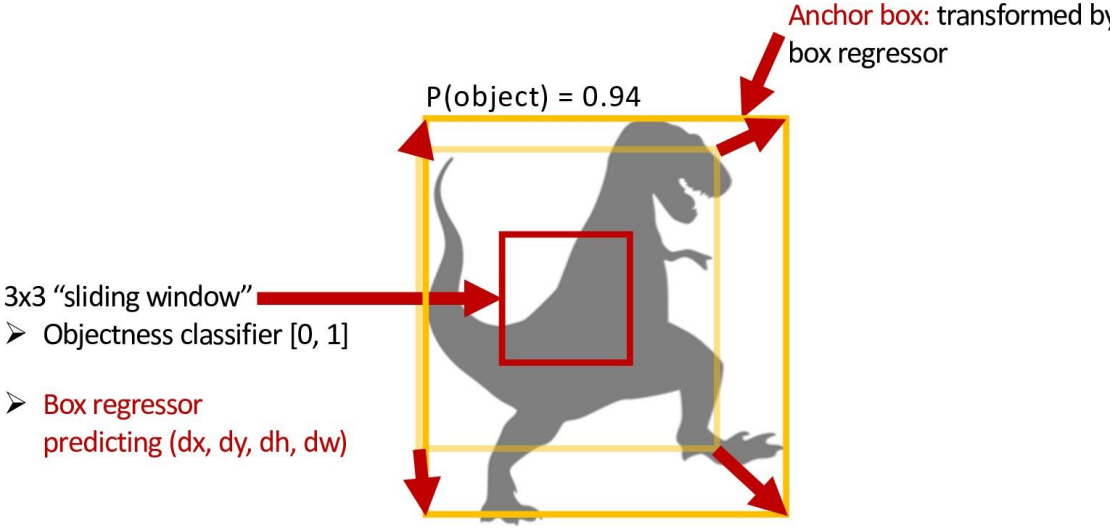


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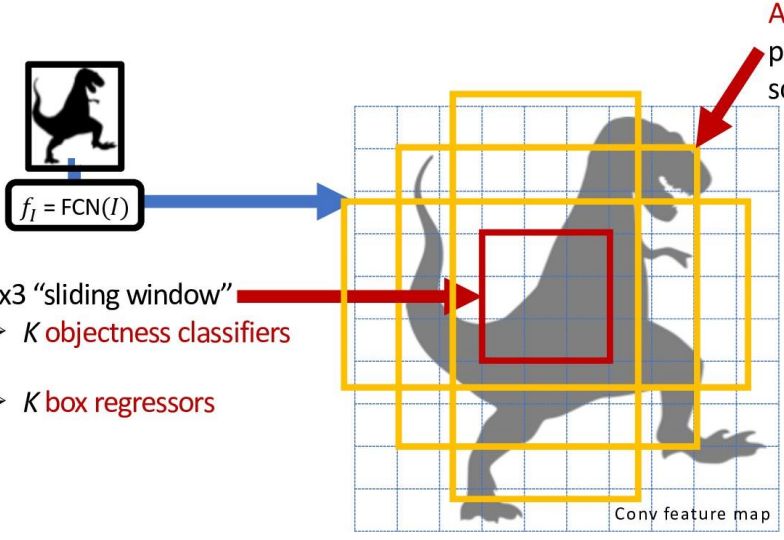


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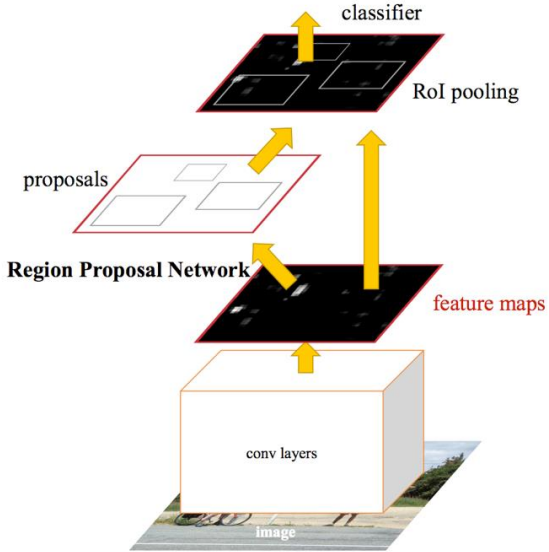
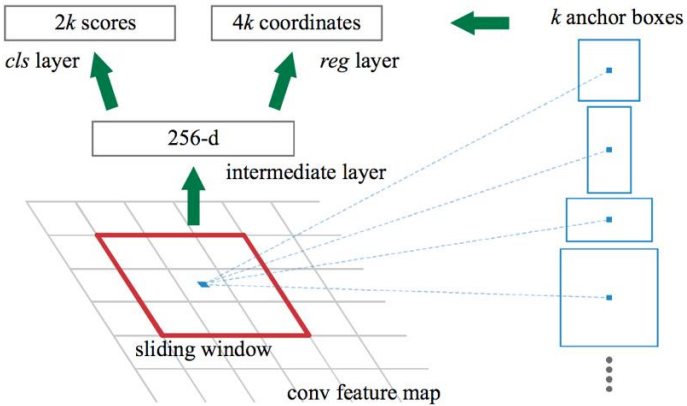
# Faster R-CNN

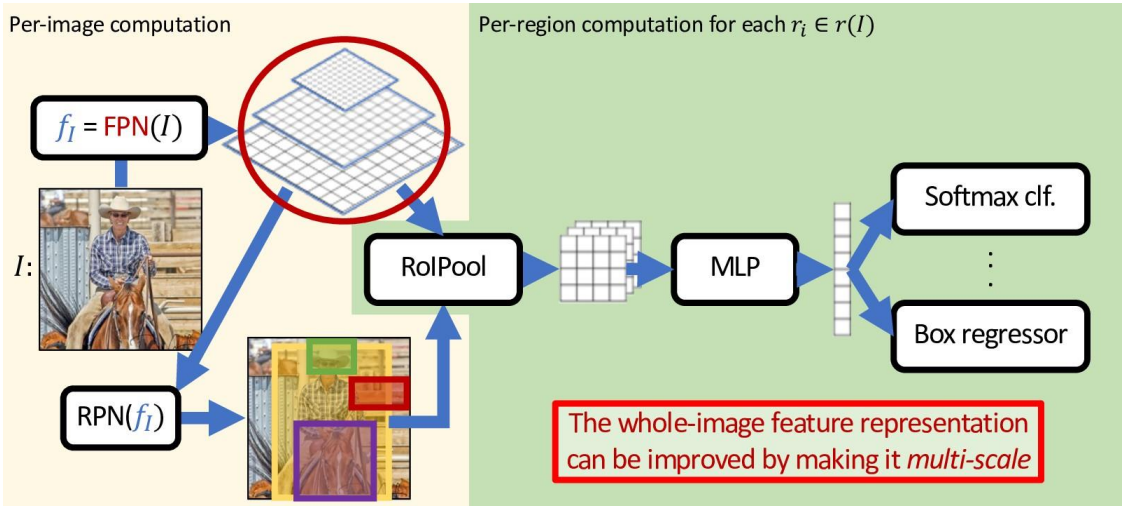

classifier
RoI pooling
proposals
Region Proposal Network
feature maps
conv layers
image

# Faster R-CNN

At each location, consider boxes of many different sizes and aspect ratios



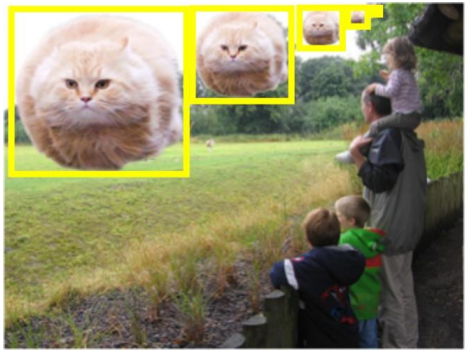
# Feature Pyramid Network




Lin, Dolla´r, Girshick, He, Hariharan and Belongie: Feature Pyramid Networks for Object Detection. CVPR, 2017.

# Feature Pyramid Network

**Goal of Feature Pyramid Network:** Improve Scale Equivariance



Detectors need to

1. classify and
2. localize

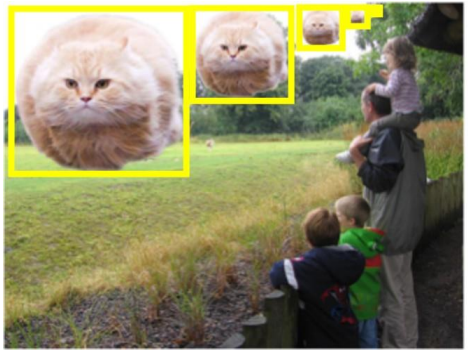
objects over a wide range of scales

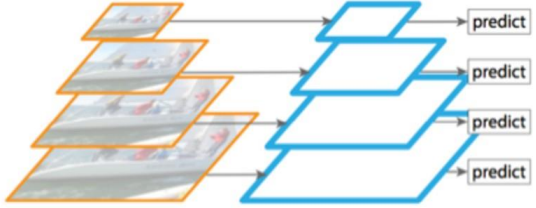
FPN improves this ability

Lin, Dolla´r, Girshick, He, Hariharan and Belongie: Feature Pyramid Networks for Object Detection. CVPR, 2017.

# Feature Pyramid Network

## Strategy 1:Image Pyramid






(a) Featurized image pyramid

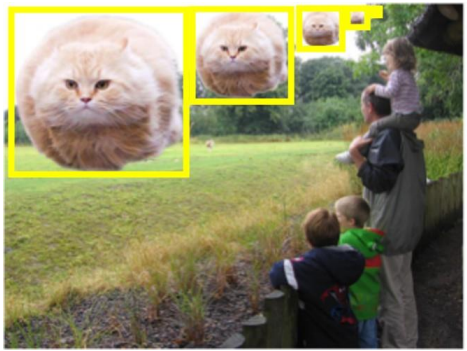
Standard solution – *slow!*

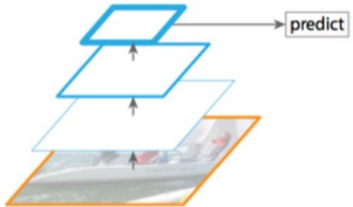
(E.g., Viola & Jones, HOG, DPM, SPP-net,

Lin, Dolla´r, Girshick, He, Hariharan and Belongie: Feature Pyramid Networks for Object Detection. CVPR, 2017.

# Feature Pyramid Network

## Strategy 2: Multi-scale Features (Single-scale Map)






(b) Single feature map

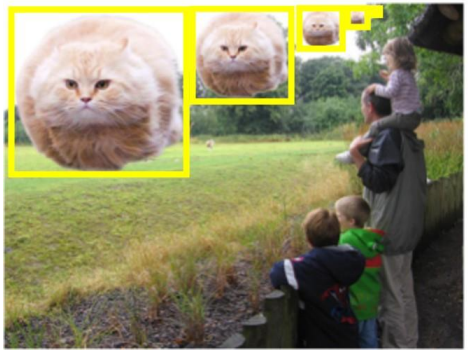
Leave it all to the features – *fast, suboptimal*

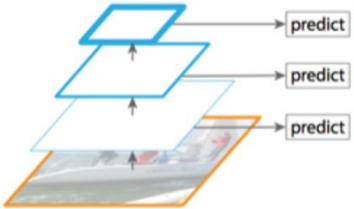
(E.g., Fast/er R-CNN, YOLO, …)

Lin, Dolla´r, Girshick, He, Hariharan and Belongie: Feature Pyramid Networks for Object Detection. CVPR, 2017.

# Feature Pyramid Network

## Strategy 3: Na¨ıve In-network Pyramid






(c) Pyramidal feature hierarchy

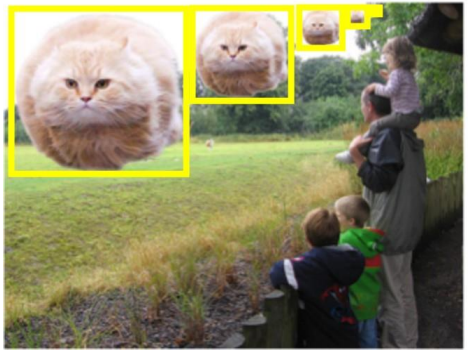
Use the internal pyramid – *fast, suboptimal*

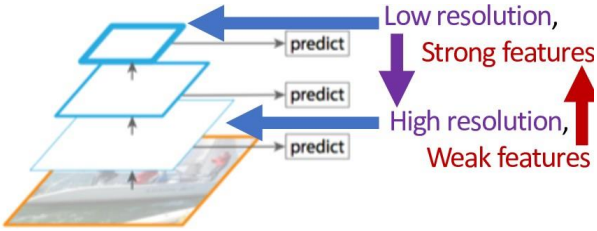
(E.g., ≈ SSD, …)

Lin, Dolla´r, Girshick, He, Hariharan and Belongie: Feature Pyramid Networks for Object Detection. CVPR, 2017.

# Feature Pyramid Network

## Strategy 3: Naive In-network Pyramid






(c) Pyramidal feature hierarchy

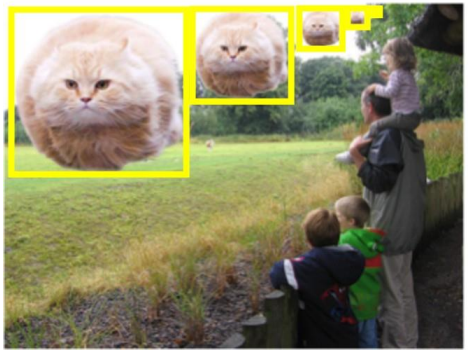
Use the internal pyramid – *fast, suboptimal*

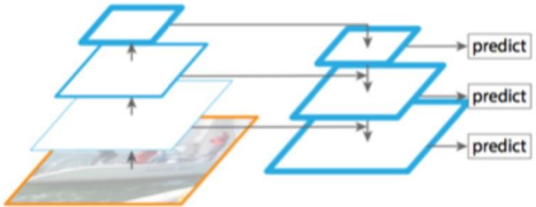
(E.g., ≈ SSD, …)

Lin, Dolla´r, Girshick, He, Hariharan and Belongie: Feature Pyramid Networks for Object Detection. CVPR, 2017.

# Feature Pyramid Network

## Strategy 4: Feature Pyramid Network





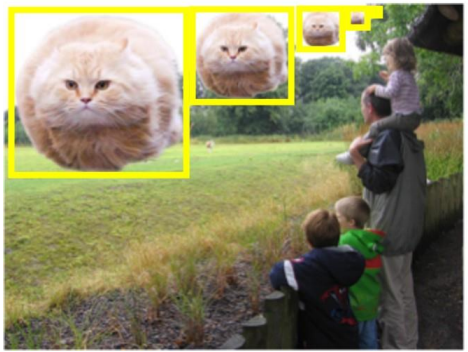

(d) Feature Pyramid Network

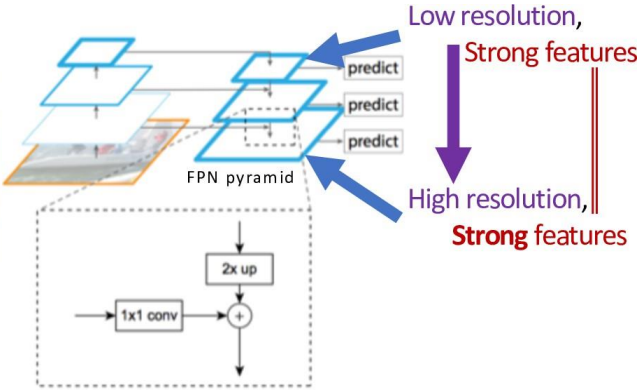
Top-down enrichment of high-res features – *fast, less suboptimal*

Lin, Dolla´r, Girshick, He, Hariharan and Belongie: Feature Pyramid Networks for Object Detection. CVPR, 2017.

# Feature Pyramid Network

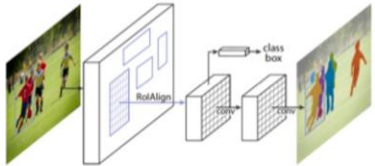
## Strategy 4: Feature Pyramid Network



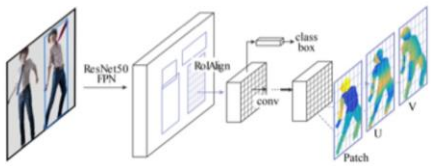



Lin, Dolla´r, Girshick, He, Hariharan and Belongie: Feature Pyramid Networks for Object Detection. CVPR, 2017.

# Generalization to other Output Modalities




**Mask R-CNN**
[He, Gkioxari, Dollár, Girshick]



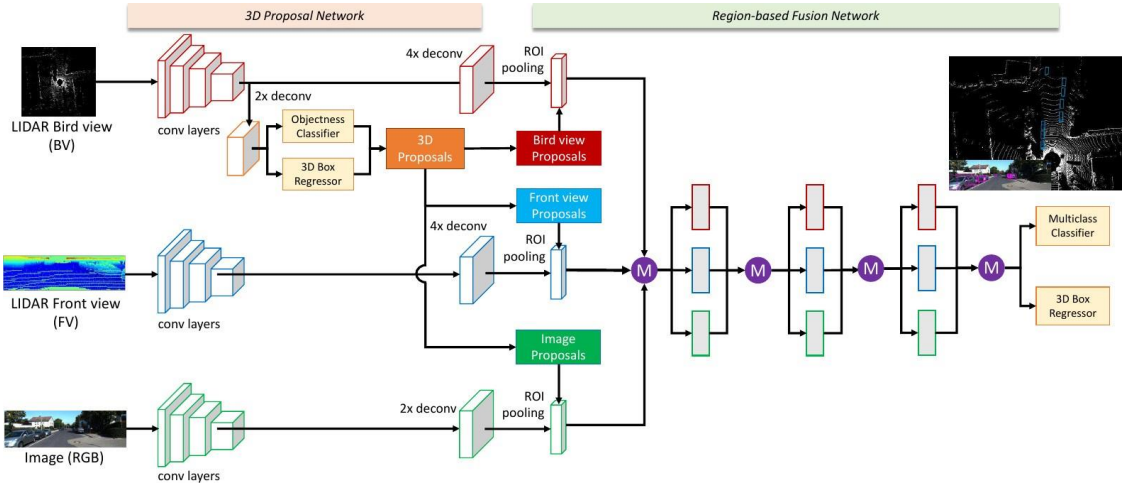

**DensePose**
[Güler, Neverova, Kokkinos]

- It is easy to add more/other output heads to this framework
  - Mask R-CNN: Predicting an instance segmentation mask per detection
  - DensePose: Predict object coordinates (think: texture map coordinates)

https://github.com/facebookresearch/Detectron

He, Gkioxari, Dolla´r and Girshick: Mask R-CNN. ICCV, 2017.

# MV3D: Combining Multiple 2D Views (RGB/Lidar Projections)




Chen, Ma, Wan, Li and Xia: Multi-view 3D Object Detection Network for Autonomous Driving. CVPR, 2017.

# Readings

► Dalal and Triggs: Histograms of Oriented Gradients for Human Detection. CVPR, 2005.

► Object Detection with Discriminatively Trained Part Based Models. Felzenszwalb, Girshick, McAllester and Ramanan. PAMI, 2010.

► Ren, He, Girshick and Sun et al.: Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. NIPS, 2015.

► Lin, Dollar, Girshick, He, Hariharan and Belongie: Feature Pyramid Networks for Object Detection. CVPR, 2017.