



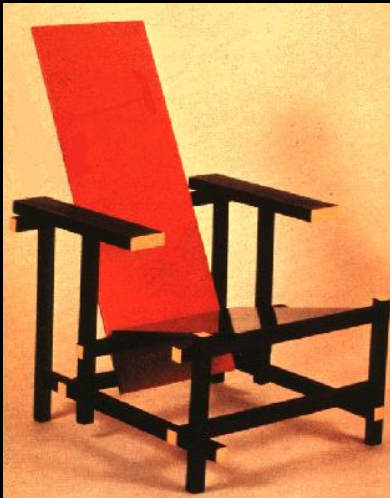
SEED

Learning to See in a Dynamic World

ERC Consolidator Grant

Cristian Sminchisescu
Lund University

Challenges: Intra-class variation



Challenges: viewpoint variation



Challenges: illumination



Challenges: Articulation and Shape of Humans



General poses with many d.o.f.

Self-occlusions

Difficult to segment the individual limbs



Different body sizes



Loss of 3D information in the perspective projection

Partial views



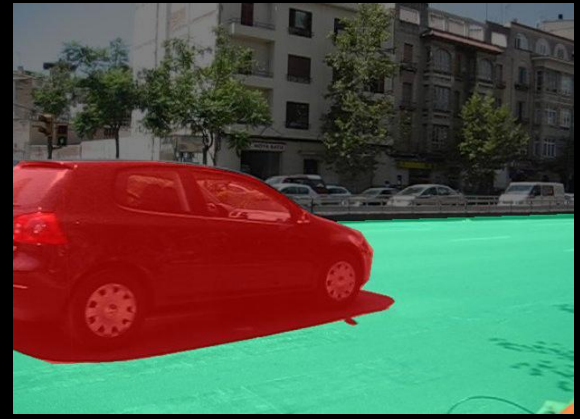
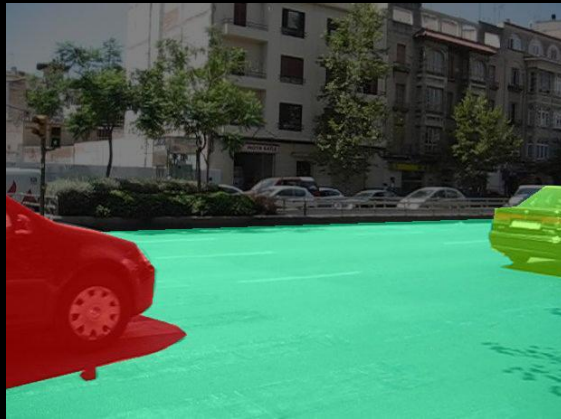
Accidental alignments
Motion blur

Several people,
occlusions

Reduced observability of
body parts due to loose
fitting clothing



Dynamic Scenes: *The complexity*



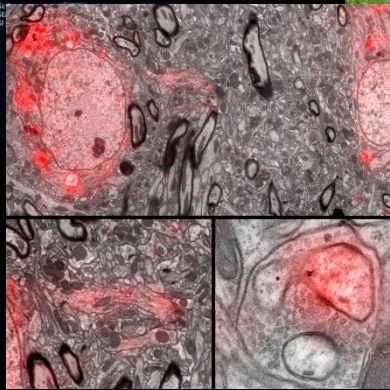
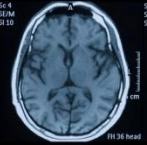
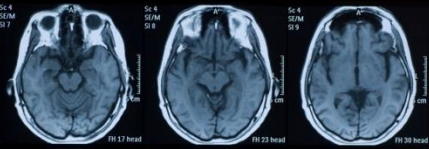
All previous ones shown for images

+

Large inter-frame displacements, occlusions

Why Machine Learning?

Defining how an object or a human looks like in images and video, under a representative set of variations, would be too difficult to specify by hand, but can be characterized by datasets with strong statistical regularity...

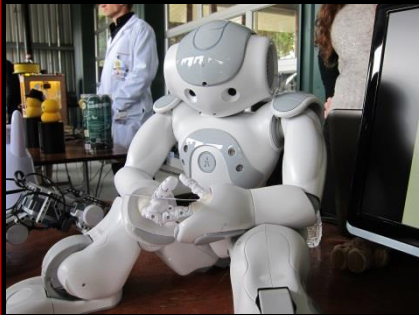


Explosion of data in science, engineering, medicine



40% of internet traffic is video

Big Data \approx Image Data



Real-time sensors



24hrs/day

8 billion



100,000 hrs/day



250 billion



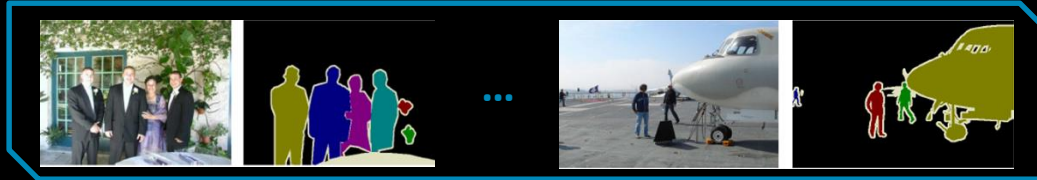


Human (infant) visual learning requires billions of images.
It is (also) a big data problem

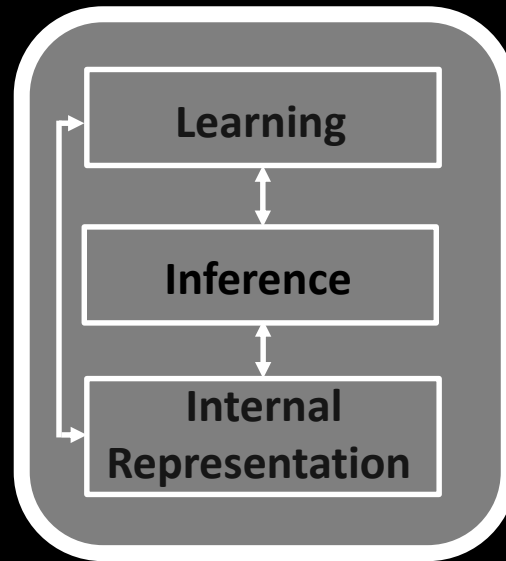
A robot may require just as much data in order to
competently learn to see and interact with the visual world

Computer Vision Modeling

Training set of (input \leftrightarrow ground truth description)



Input (query)

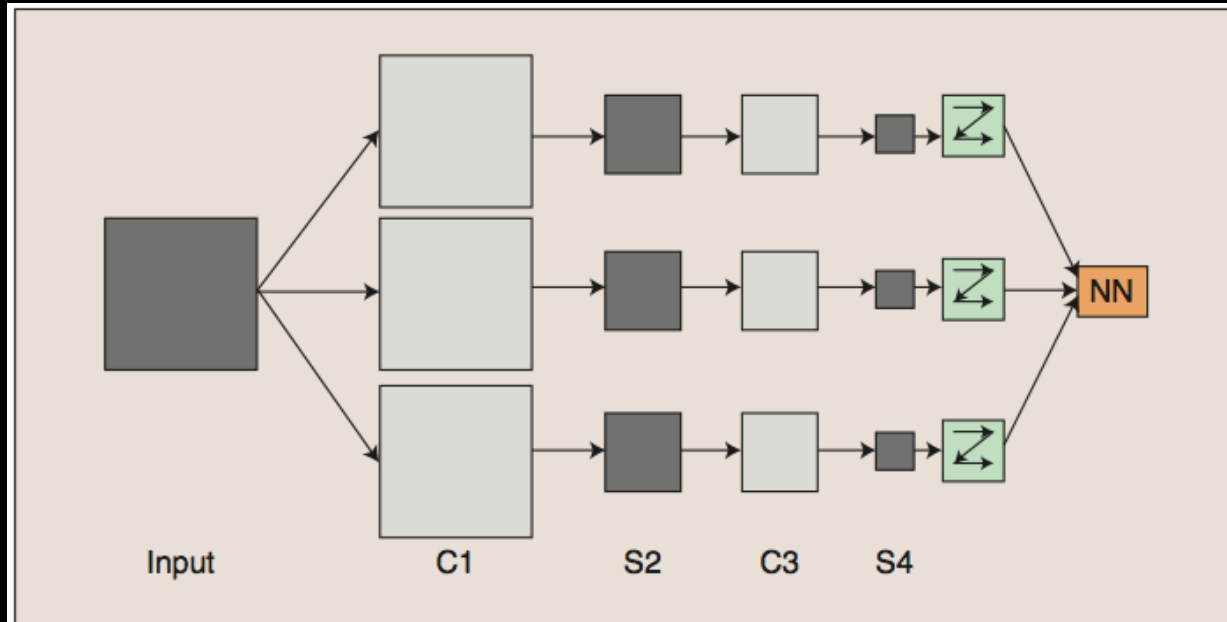


Output (description)

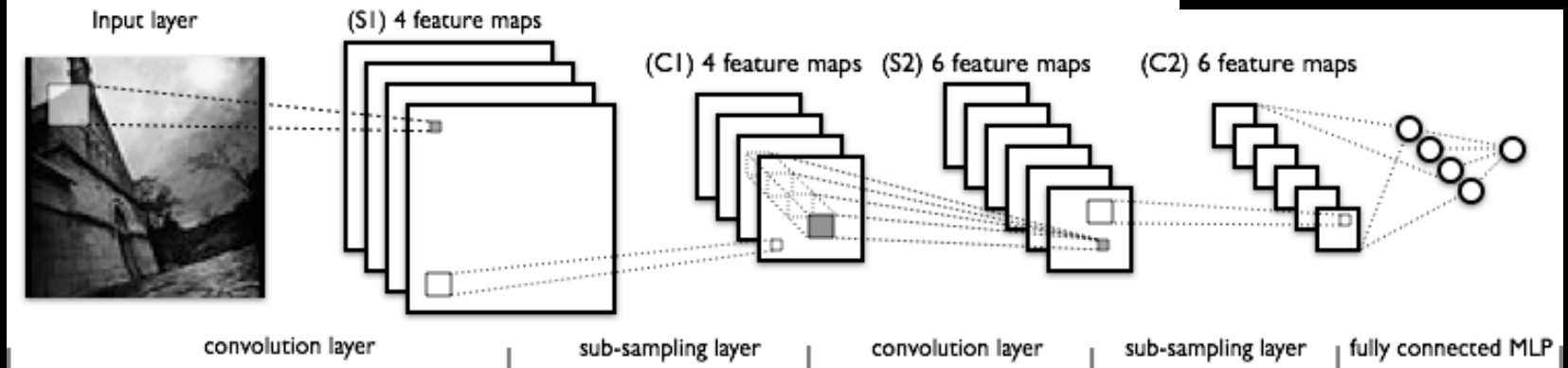


Learning Visual Representations

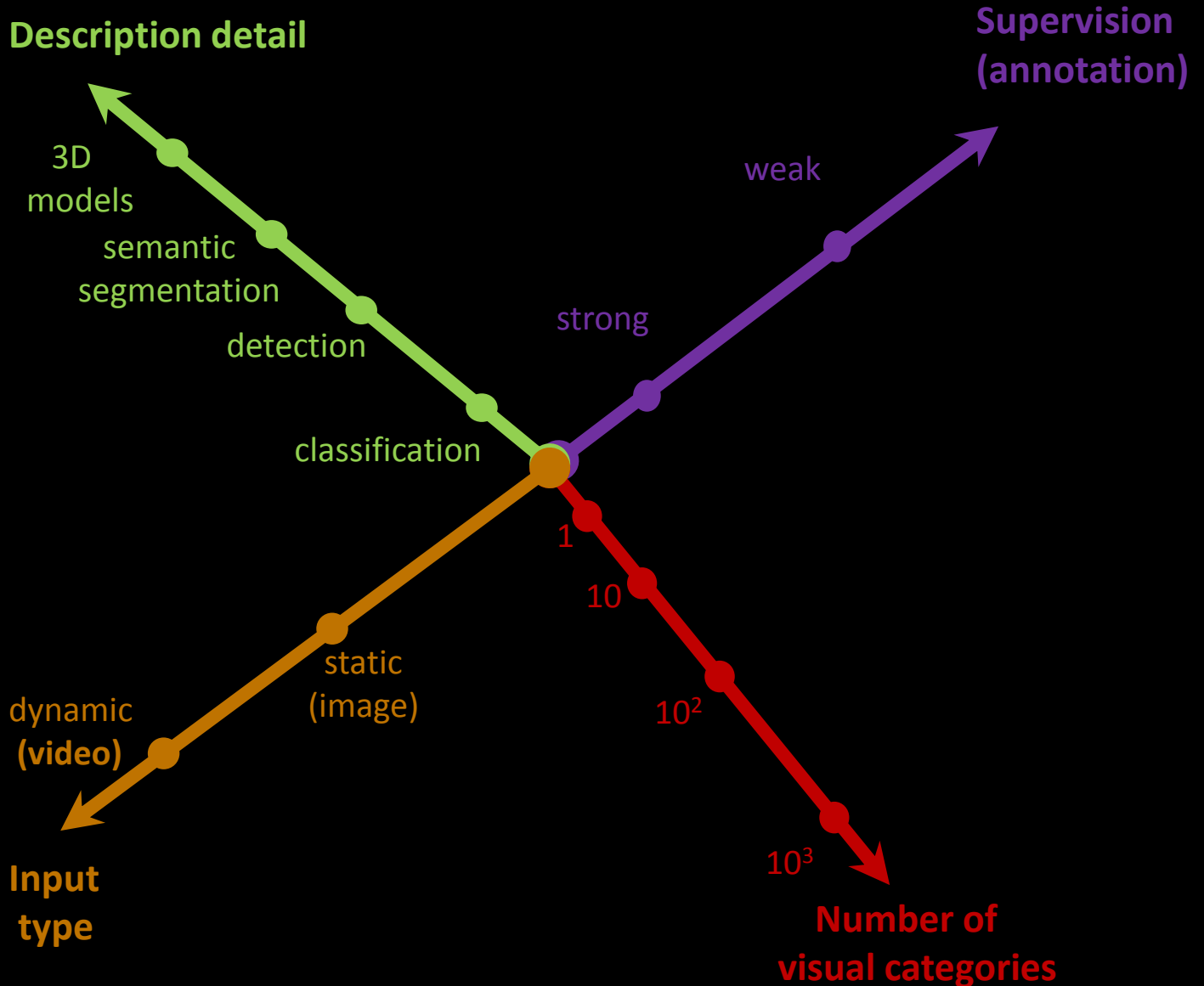
Convolutional Neural Networks



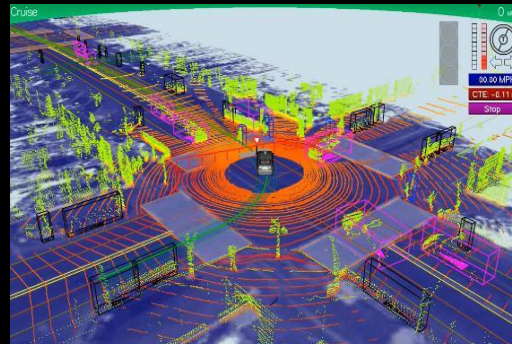
C layers are convolutions, **S** layers pool/sample



Scientific Challenges



Research Emphasis



Computers that 'learn to see' in a dynamic world

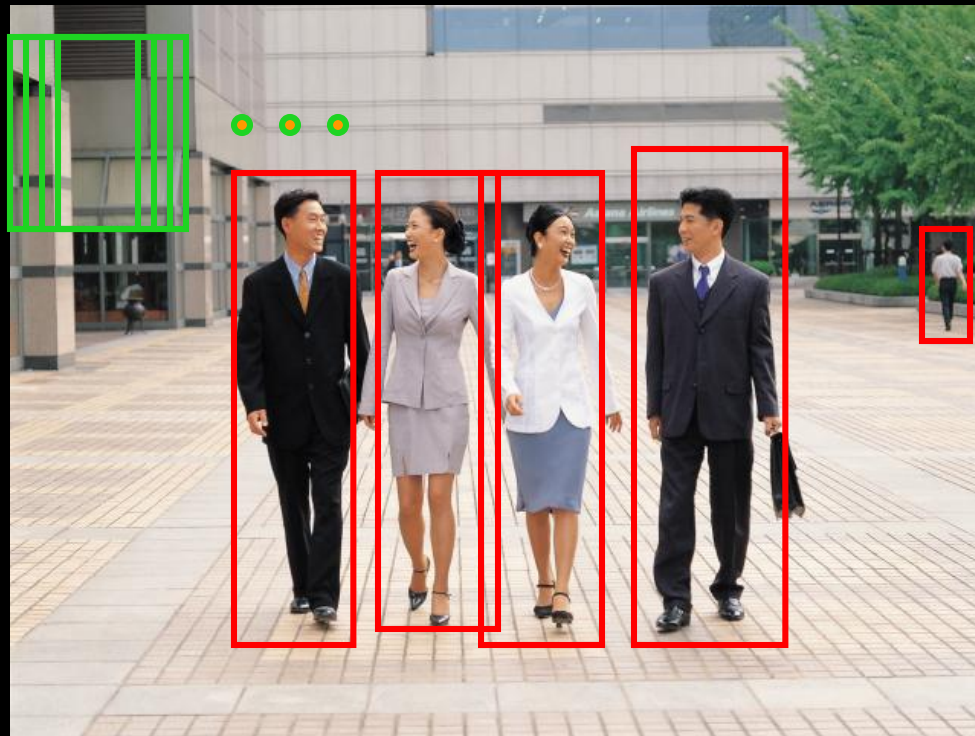
Static (image) → **Dynamic** (*video*)

Coarse analysis (holistic) → **Precise** description (*shape, 3D*)

Rigid (preset supervision) → **Flexible** (*continuous learning*)

Recognition by Detection

Is this an X?



Search at multiple locations, scales and for all object categories of interest
Indiscriminately describe (mix) both foreground and background

Recognition in the Human Eye



Active Visual Recognition

White = Fixation rectangles (attention)
Black = Accumulated evidence so far (class-specific history)
Colored = Final detections
* = Not shown in visualization

0) Get init state based on input image *



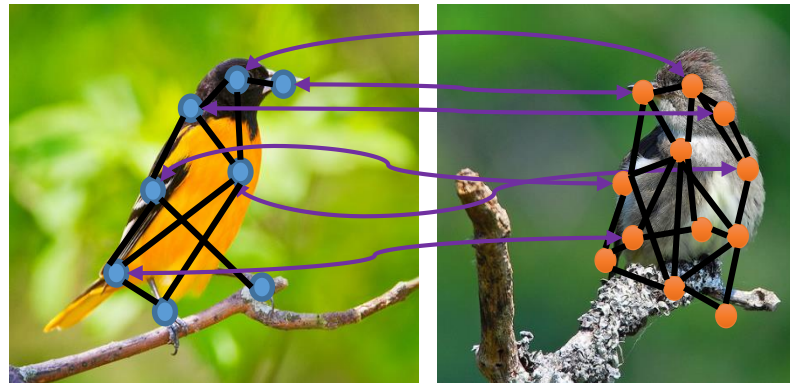
Deep reinforcement learning for the
search strategy + detector + stopping criteria

Pirinen and Sminchisescu, CVPR 2018

ESTABLISHING CORRESPONDENCES GRAPH MATCHING

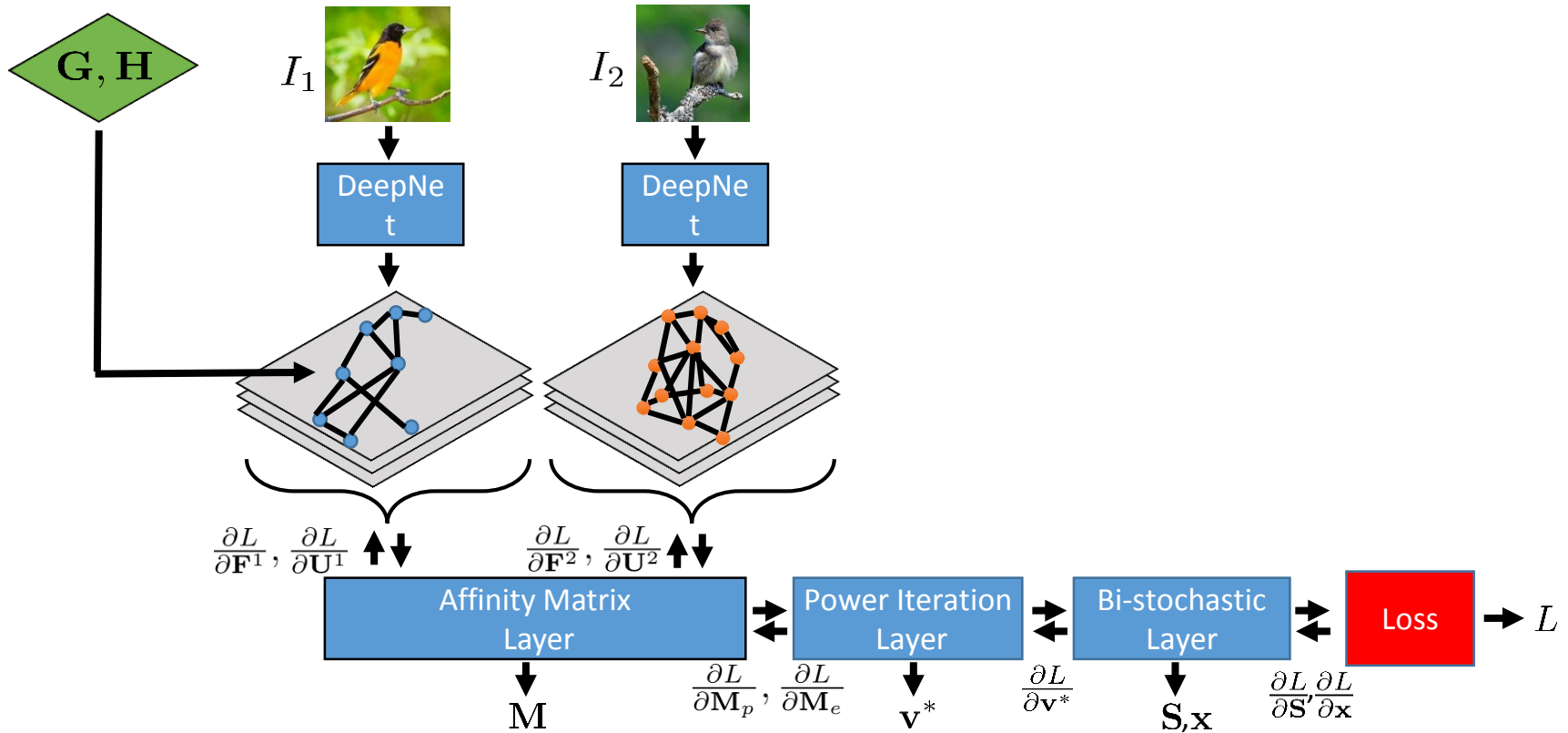
Input: two graphs $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$

with $|V_1| = n, |V_2| = m, |E_1| = p, |E_2| = q$



Task: find a one-to-one mapping between the two graphs
that accounts for **structure**, i.e. reflects both node and edge
similarities

TRAINABLE GRAPH MATCHING NETWORK



Matrix backpropagation: generalization of backprop to matrix functions and global calculations like SVD, EIG, projectors (Ionescu, Vanzos, Sminchisescu, ICCV 2015)

Trainable either on different images of the same video or same visual category



MPI-Sintel test partition exhibits large motions and occlusion areas

From top to bottom: source images with the initial grid of points overlaid and target images with corresponding matches. Colors are unique and encode correspondences. Even for fast moving objects, points tend to track the surface correctly, without sliding – see the dragon's wing, claw, and the flying monster

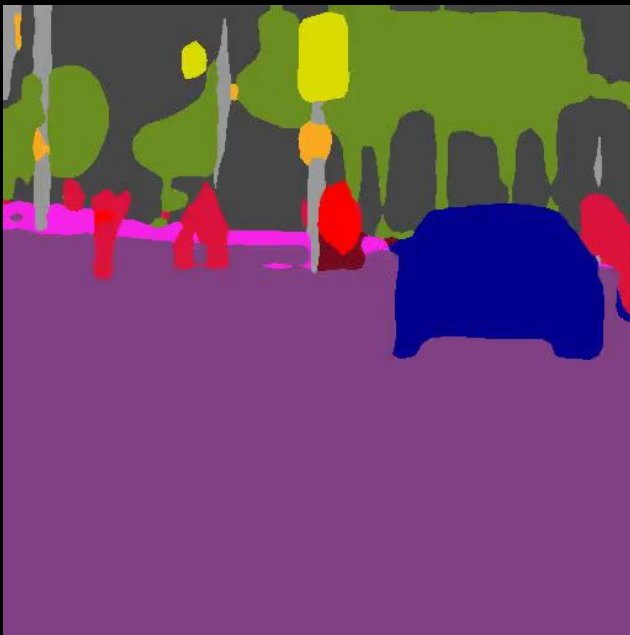
CUB: Green frames indicate ground truth correspondences, red frames estimates



Other correspondence results on arbitrary images



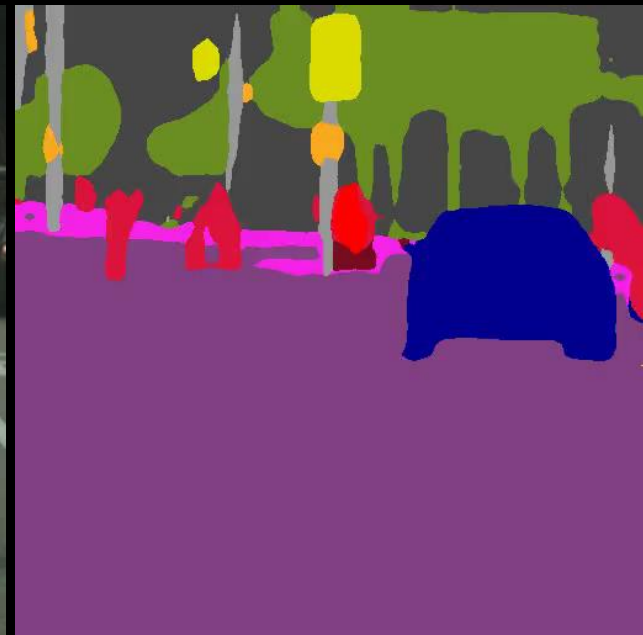
Weakly-supervised Semantic Video Segmentation



Per Frame

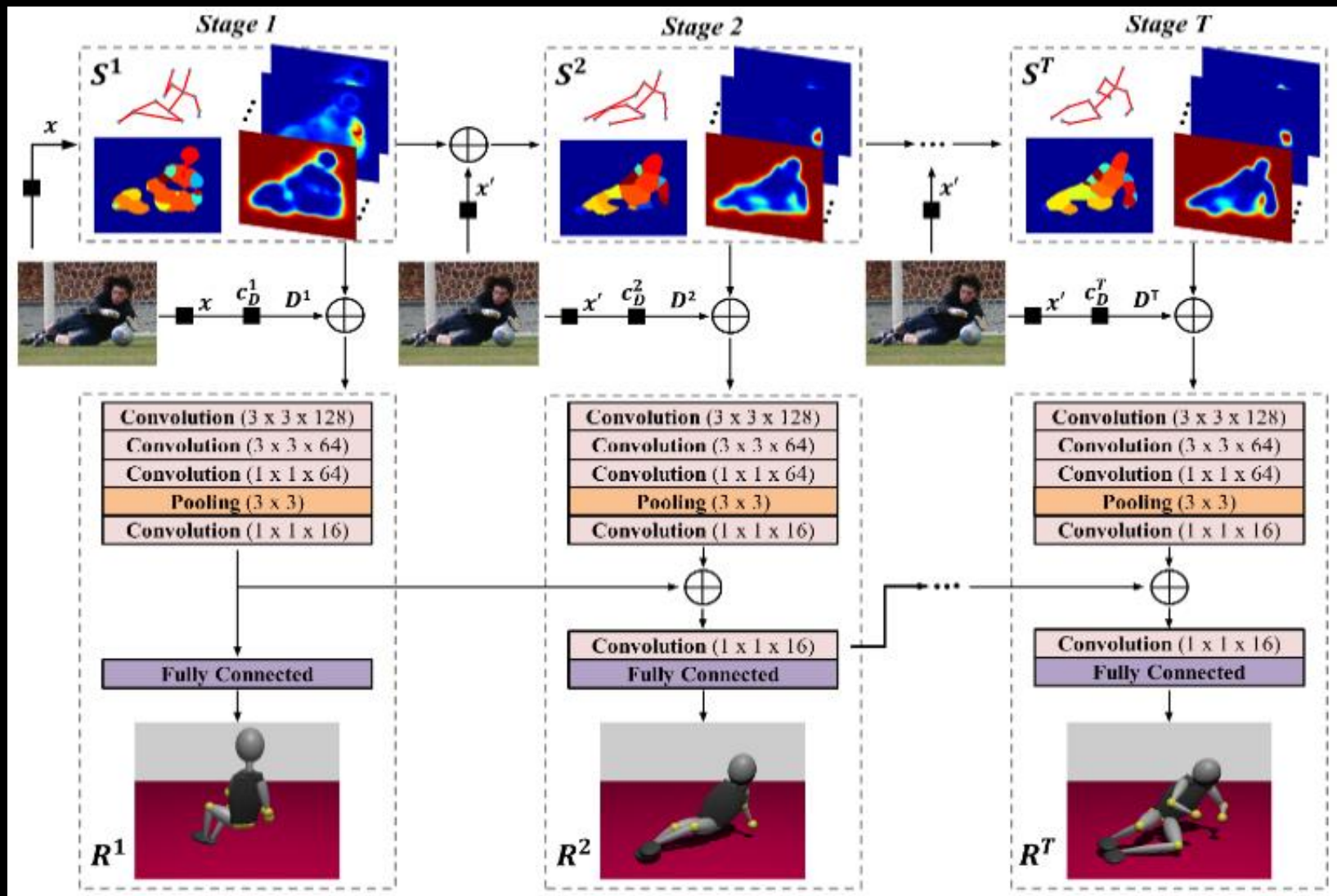


Original Video

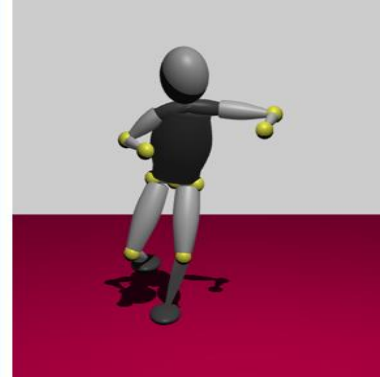
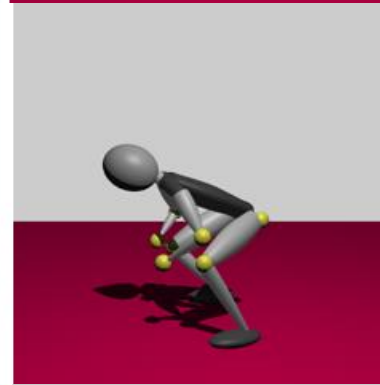
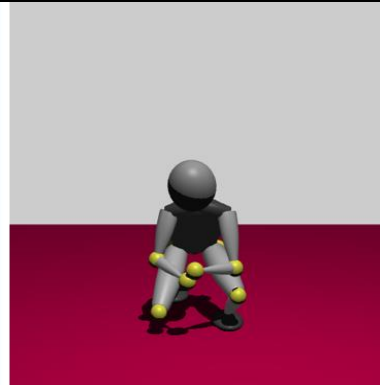
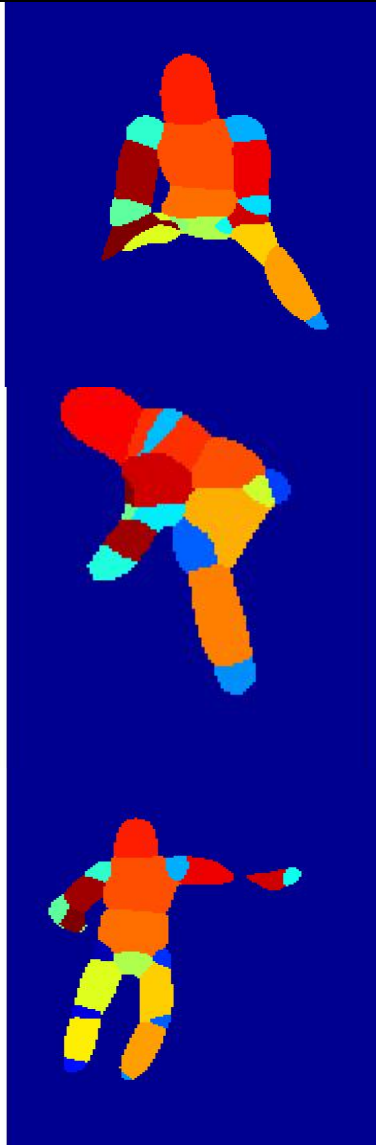
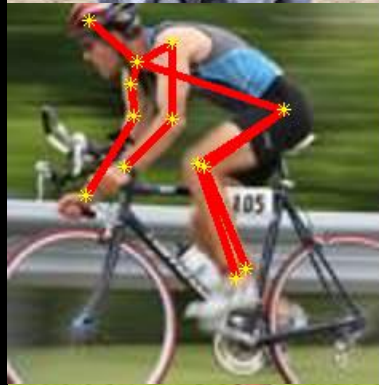


Proposed (GRFP)

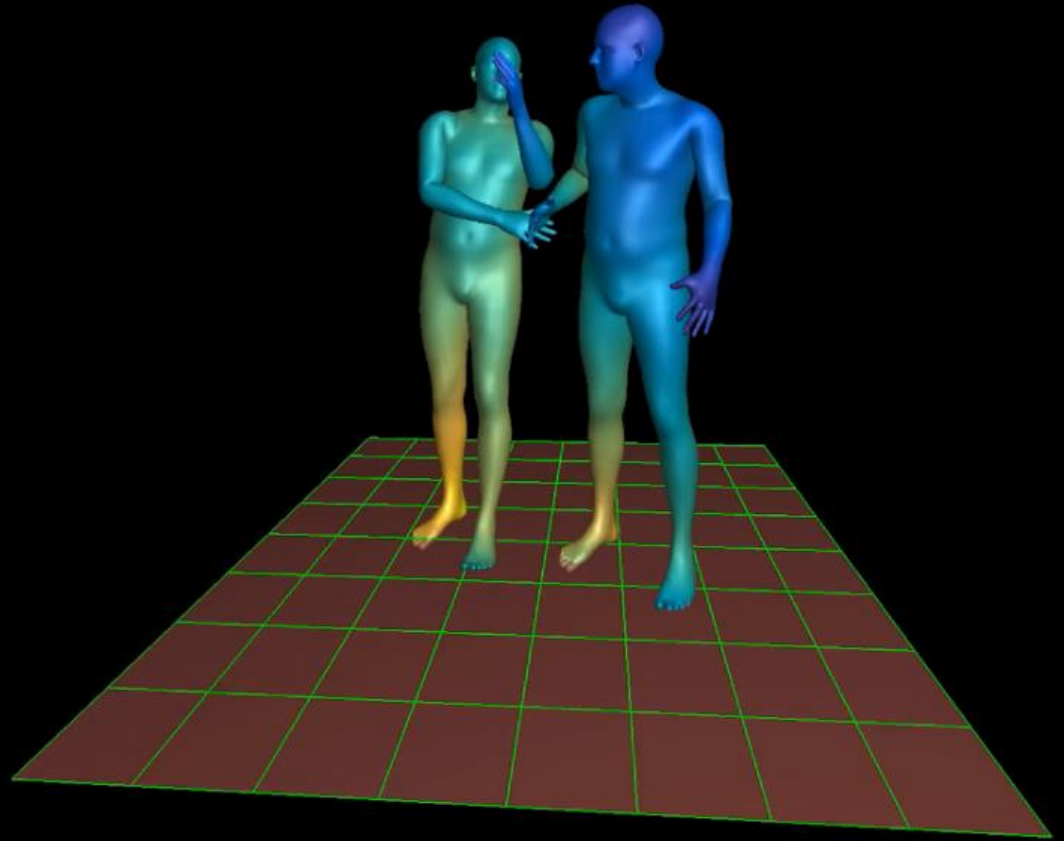
Multitask Sensing Architecture

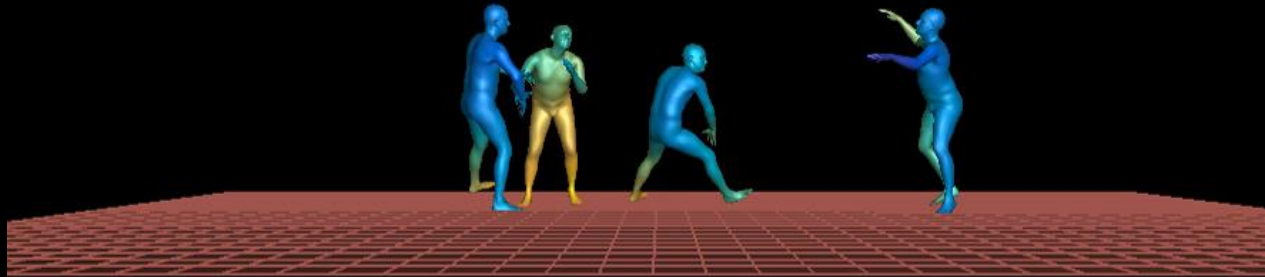


Semantic Segmentation + 3D



Multiple People, 3D Pose and Shape





Autism Treatment Automation



Camera placed behind robot to avoid interference with therapy

Field of view must avoid robot

Chairs of child and therapist need to be close to table to use cards

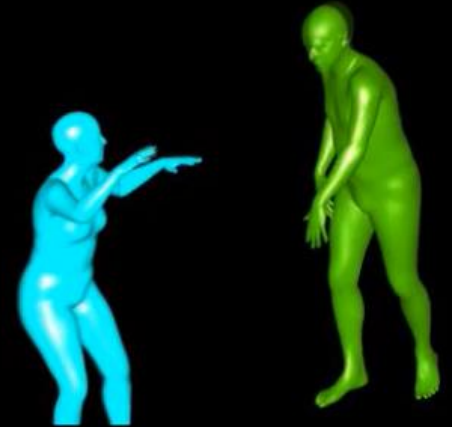


Child and therapist out of field of view



Interaction results in occlusions

Reconstructing Human Interactions



Behavior: Valence Arousal



AI Aspects

- Societal
 - Adapted new degree [programs and continuous instruction, well-balanced regulatory framework]
- Scientific enablers
 - Learning theory (dynamics and nonlinear systems), weak supervision, perception and action in non-trivial environments
- How can pitfalls be avoided?
 - Critical understanding of potential and limitations/evolution. Adapt and communicate, adequate data collection (unbiasedness), privacy
- Multidisciplinary aspects
 - Huge potential but domain knowledge is key
- Time perspective
 - Active/robotics, personalization

Thank you!

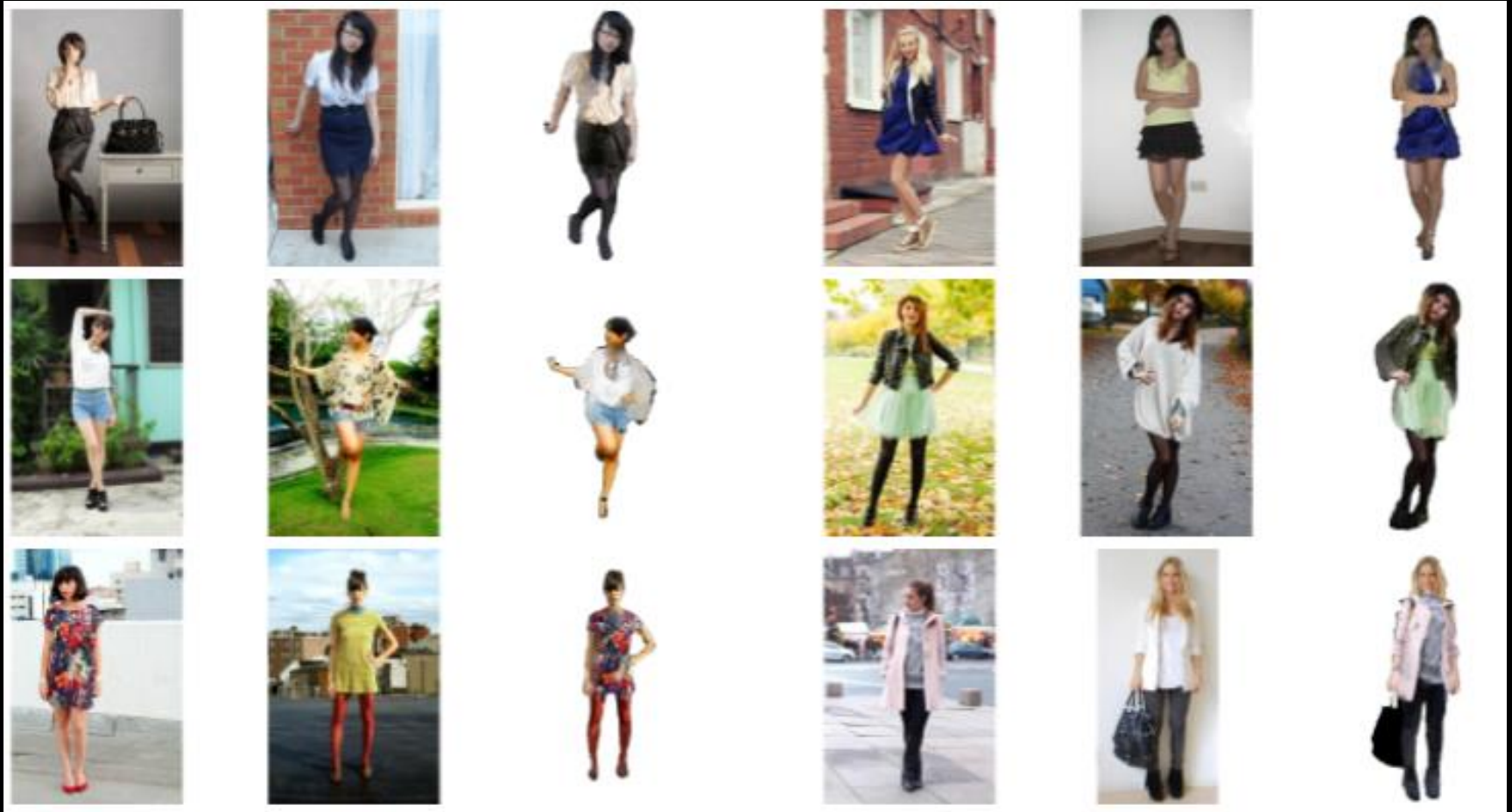


Human Appearance Transfer



Given two people **differently dressed** and in **different poses**, swap appearance

Human Appearance Transfer



Dress a person with clothing from another

Human Appearance Transfer



Dress Like a Celebrity

Celebrity



Regular person



Regular person dressed as celebrity



Impact

- ERC team of 4 members established (part of a larger research group of 10 people)
- 10 publications at CVPR, NIPS, AISTATS
 - 1 best paper award honorable mention (CVPR18, highest impact conference in AI)
- ECCV 2018 organization (Program Chair)
- Presentations at ETHZ, INRIA, Stanford, Heidelberg, Max Planck, Edinburgh, etc.

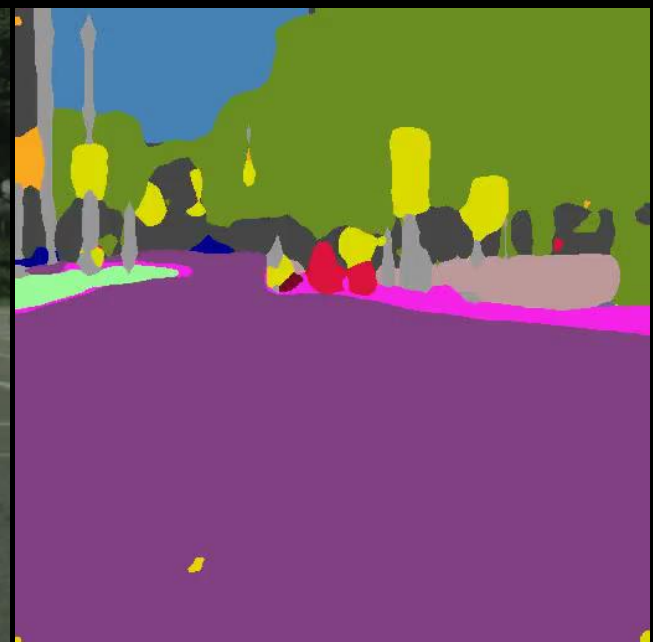
Semantic Video Segmentation (II)



Per Frame



Original Video



Proposed (GRFP)

3D Human Training Data

- Labeled 2d and 3d human training data difficult to acquire
- Accurate 2d can be captured and labeled by hand (e.g. body joints) – not really ground truth but good enough
- Motion capture synchronized 2d-3d is extremely accurate but backgrounds/clothing not as diverse
- Mixed reality training dates back at least to 2001 but realism of both body and geometric scene is essential

Do we need fully labeled data... or can work with whatever available within a multitask architecture?