Photorealistic image synthesis for object instance detection

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Image classification

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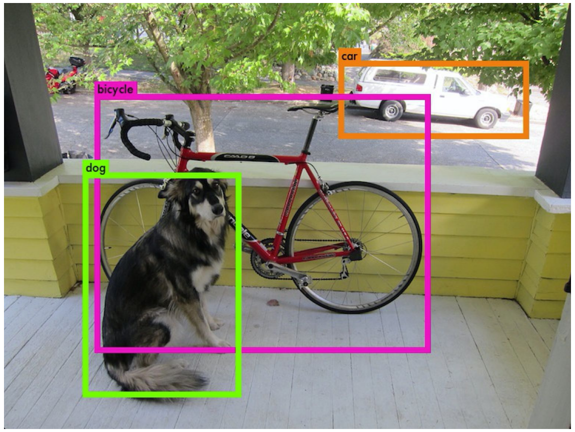
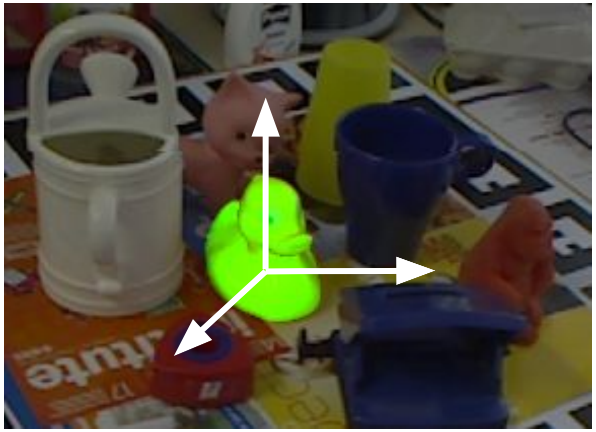


Object detection

$$



6D object pose estimation

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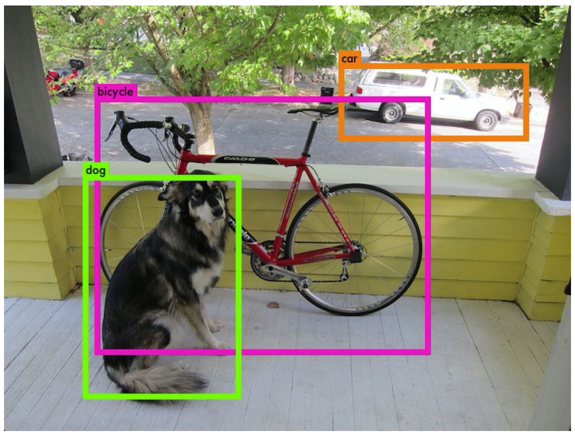

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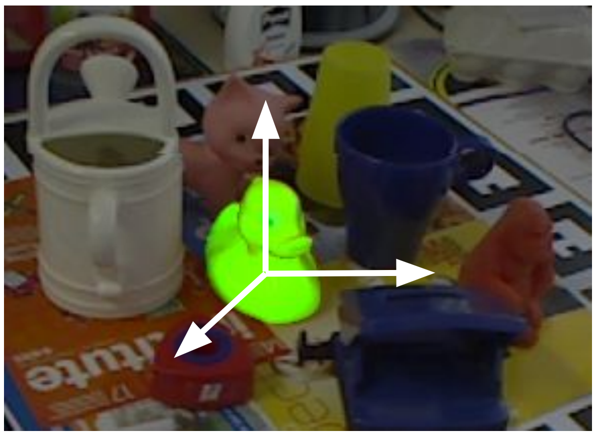

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Training with **synthetic images**?

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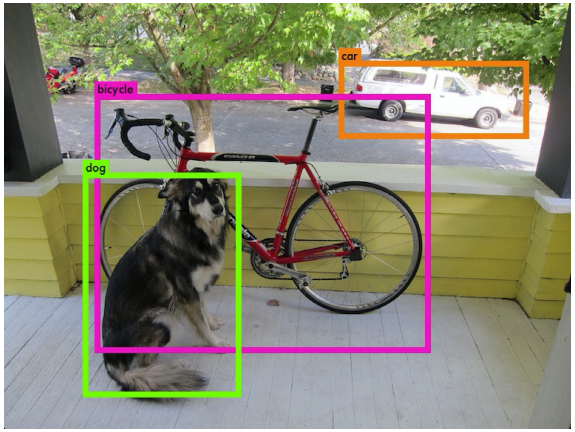

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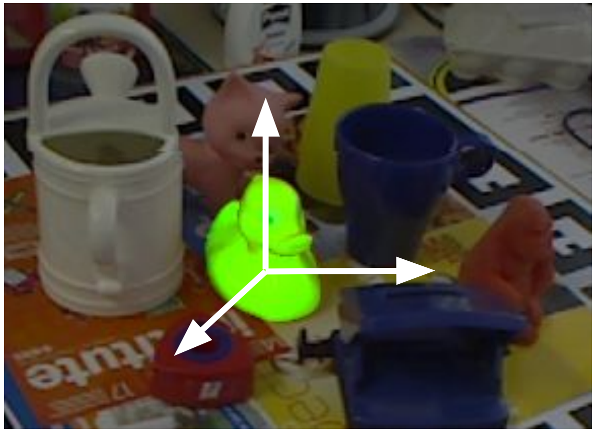

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Training with **synthetic images**?

Scales well as only minimal human effort is required.

Common approaches to synthesize training images

Approach 1: **Cut & paste on photographs**

Object segments cut from real images

Background photographs

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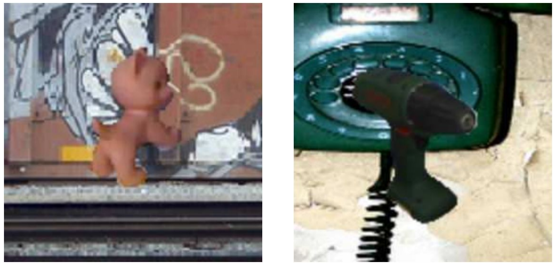
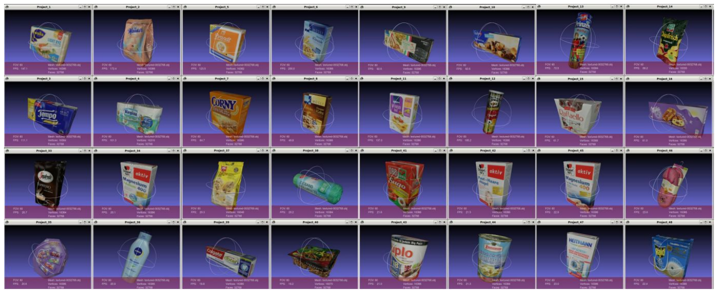
Object detection
Dwibedi ICCV’17, Dvornik ECCV’18



6D object pose estimation
Rad ICCV’17, Tekin CVPR’18

Common approaches to synthesize training images

Approach 2: **Rendering 3D object models on photographs**



3D object models

Background photographs

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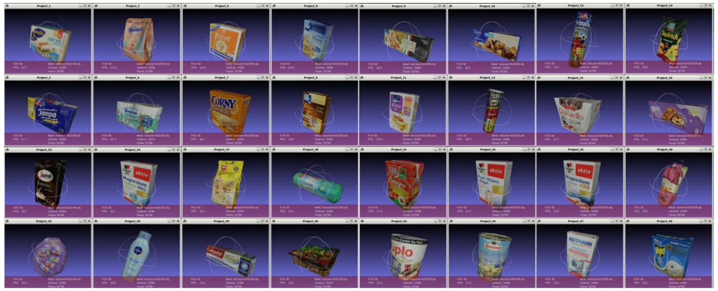
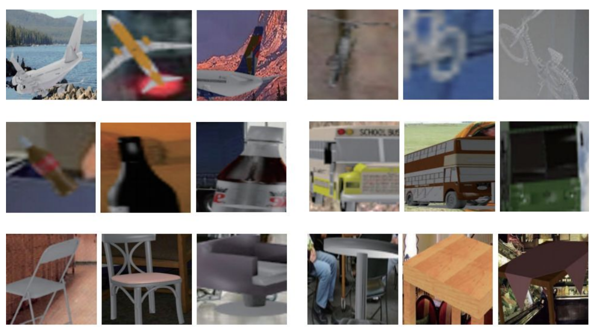


3D object models

Background photographs

Object detection
Hinterstoisser ICCVW'19



Viewpoint estimation
Su ICCV'15

Optical flow estimation
Dosovitskiy ICCV'15

Problem: lack of photorealism

Inconsistent lighting of the objects and the background scene.

Missing interreflections and shadows.

Unnatural object pose and context.

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→ **Domain gap between the synthetic and real images.**

→ **Low performance on real when trained only on synthetic.**

Su ICCV'15: Render for CNN: viewpoint estimation in images using CNNs trained with...
Richter ECCV'16: Playing for data: Ground truth from computer games.
Rozantsev TPAMI'18: Beyond sharing weights for deep domain adaptation.

Reducing the domain gap

Domain adaptation (DA): Learning domain invariant features or transferring models from one domain to another (Csurka’17).

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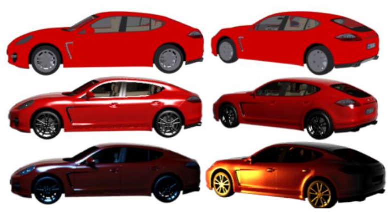
a) Rasterization techniques - e.g. OpenGL, DirectX



Viewpoint estimation
Attias ECCV'16

6D object pose estimation
Tremblay CoRL'18

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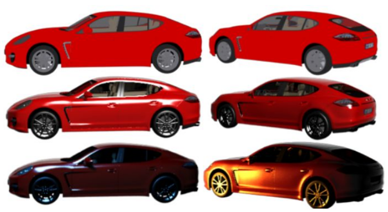

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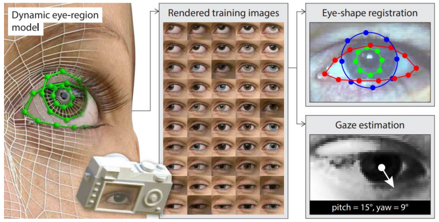
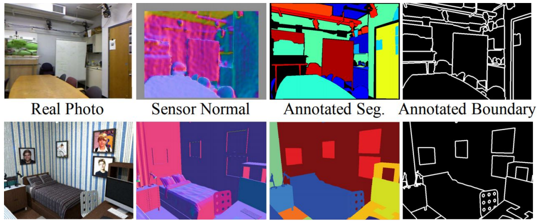
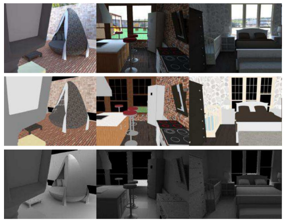
b) Physically based rendering (PBR) - e.g. Arnold, Mitsuba



Gaze estimation
(Wood ICCV'15)



Segmentation, normal estimation, boundary detection
(Zhang CVPR'17)



Intrinsic image decomposition
Li ECCV'18

Rendering techniques

Rasterization - e.g. OpenGL, DirectX

- ✔️ Fast (multiple VGA frames per second).
- ❌ Custom shaders to approximate complex illumination effects (scattering, refraction and reflection) yield difficult-to-eliminate artifacts.

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Physically based rendering - e.g. Arnold, Mitsuba

- ✔️ Ray tracing to accurately simulate complex illumination effects.
- ✔️ Highly realistic images, difficult to distinguish from real images.
- ❌ Slow (may take multiple minutes per VGA frame).

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The proposed approach for synthesis of training images:

1. **3D object models rendered in 3D models of scenes** with realistic PBR materials and lighting.
2. **Plausible geometric configuration** of objects and cameras in a scene generated using physics simulation.
3. **High photorealism** of the synthesized images achieved by PBR.

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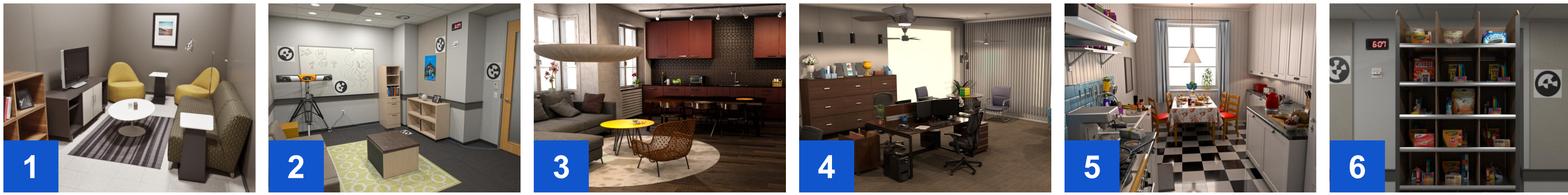
Applicable to other object-centric tasks such as instance segmentation and 6D object pose estimation.

Scene and object modeling

3D scene models: Indoor scenes with PBR materials.



Reconstructions of real scenes
(using LIDAR, photogrammetry
3D scans, PBR material scanning)

Purchased online

Shelf from APC
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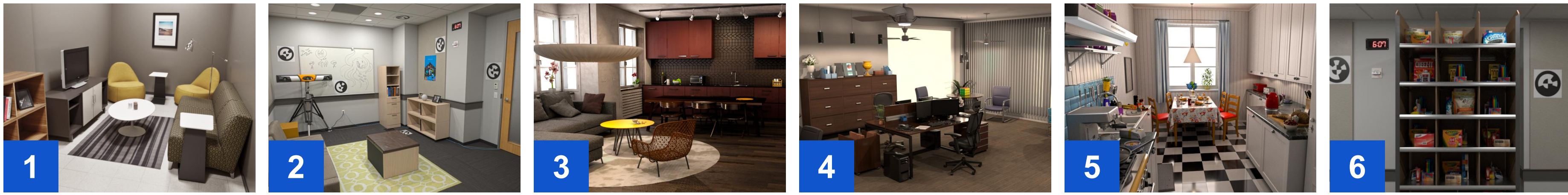

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3D object models: From Linemod and Rutgers APC datasets with assigned PBR materials.

Linemod objects
(rendered in scenes 1-5)

Rutgers APC objects
(rendered in scene 6)

Scene and object composition

Stages for objects: Manually defined polygons on scene surfaces (tables, chairs, etc.) to place the objects on.

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Generating object arrangements:
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Camera positioning: Multiple cameras are positioned around each object arrangement.

Physically based rendering

Rendered on a CPU cluster with 400 nodes (16-core processors).

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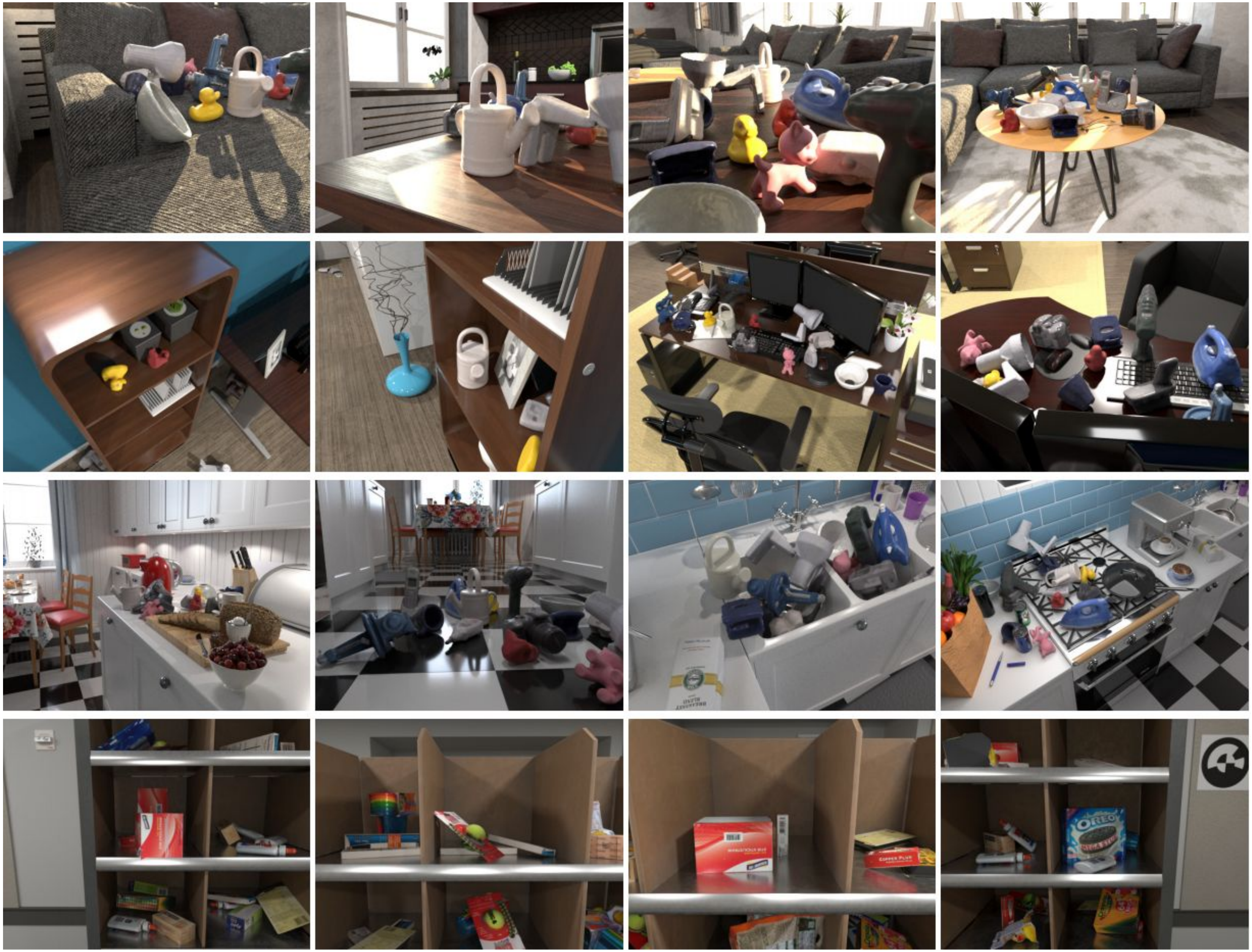
PBR images of 3 quality settings rendered from each camera:

1. **Low:** ~15s per image, 2.3M images per day.
2. **Medium:** ~120s per image, 288K images per day.
3. **High:** ~720s per image, 48K images per day.

Low quality

High quality

Examples of rendered images



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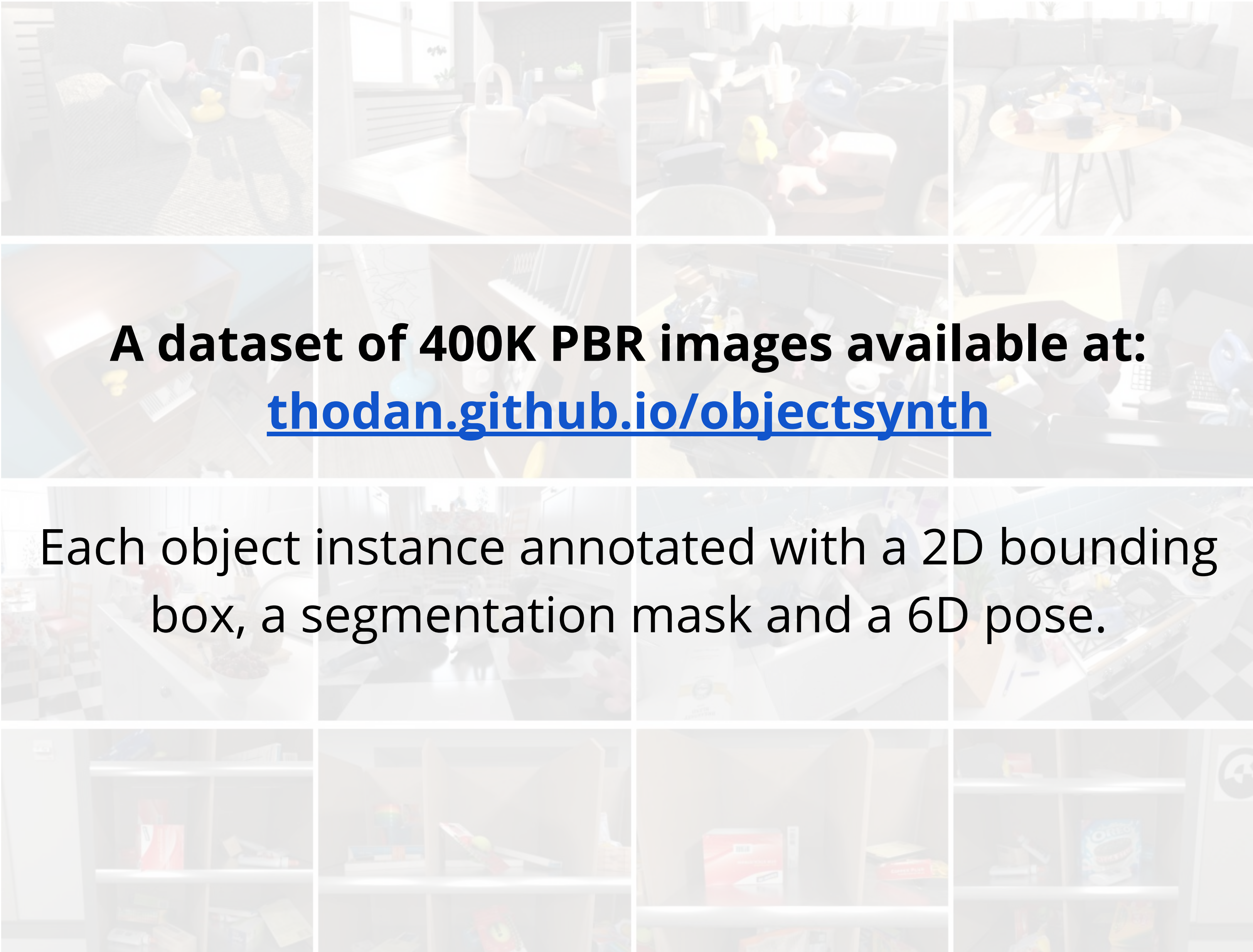

A dataset of 400K PBR images available at:
thodan.github.io/objectsynth

Each object instance annotated with a 2D bounding box, a segmentation mask and a 6D pose.

Experiments: Datasets

Linemod-Occluded (Hinterstoisser ACCV’12, Brachmann ECCV’14)

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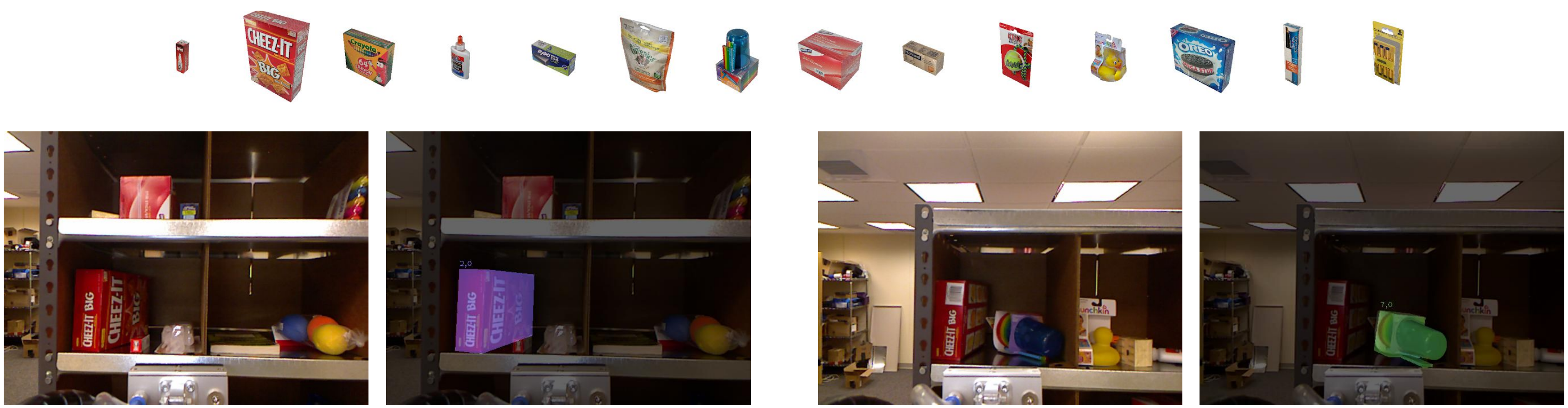
Rutgers APC (Rennie RAL'16)



Experiments: Baseline training images (BL)

Object models rendered (OpenGL) on **random photographs**,
as in Hinterstoisser ECCVW'18.

Baseline
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Object models rendered (OpenGL) on **random photographs**, as in Hinterstoisser ECCVW'18.

Baseline training images

Object models rendered in **the same poses** as in the PBR images.

Corresponding PBR images

Experiments: Importance of PBR images

Dataset	Architecture	PBR-h	PBR-l	PBR-ho	BL
LM-O	Inc.-ResNet-v2	55.9	49.8	–	44.7
	ResNet-101	49.9	44.6	–	45.1
RU-APC	Inc.-ResNet-v2	71.9	72.9	58.7	48.0
	ResNet-101	68.4	65.1	51.6	52.7

Performance (mAP@.75IoU) of Faster R-CNN (Ren NIPS'15).

High-quality PBR images outperform **BL** images by **5-11%** on Linemod-Occluded and **16-24%** on Rutgers APC.

Experiments: Importance of PBR quality

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No significant improvement on Rutgers APC objects rendered in the simpler scene 6. ➞ **The low PBR quality is sufficient for scenes with simpler illumination and materials.**

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Example real test image

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In context images outperform **out of context** images by **13-16%**.

Conclusions

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