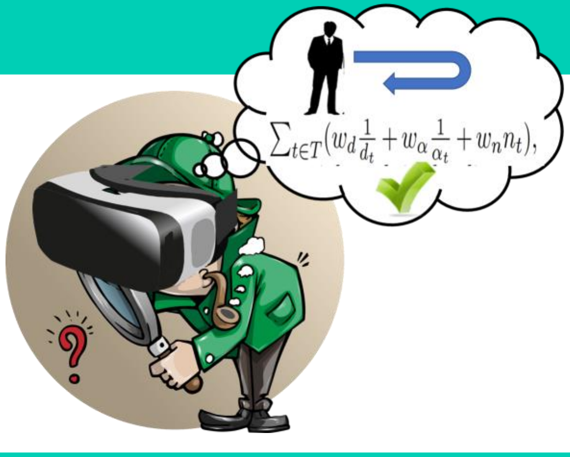
Toolset for Run-time Dataset Collection of Deep-scene Information

Gustav Aaro, Linköping University, Sweden

Daniel Roos, Linköping University, Sweden

Niklas Carlsson, Linköping University, Sweden



Proc. IEEE MASCOTS Workshop, Nov. 2020

First example scenario

Detective

Potential eye-witnesses

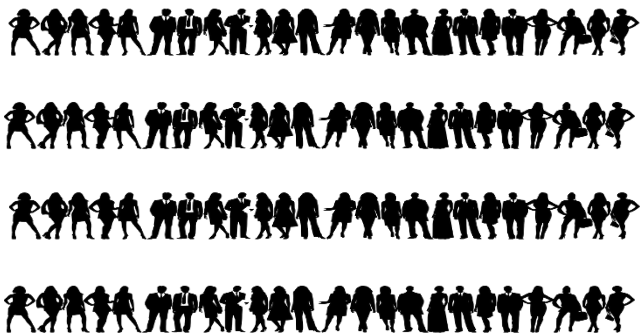
Second example scenario

Detective

Potential eye-witnesses

Second example scenario

Probability observed objects and things ??



Detective

Potential eye-witnesses

Contributions

- Methodology and software tool for generating run-time datasets capturing a user’s interactions with 3D environments

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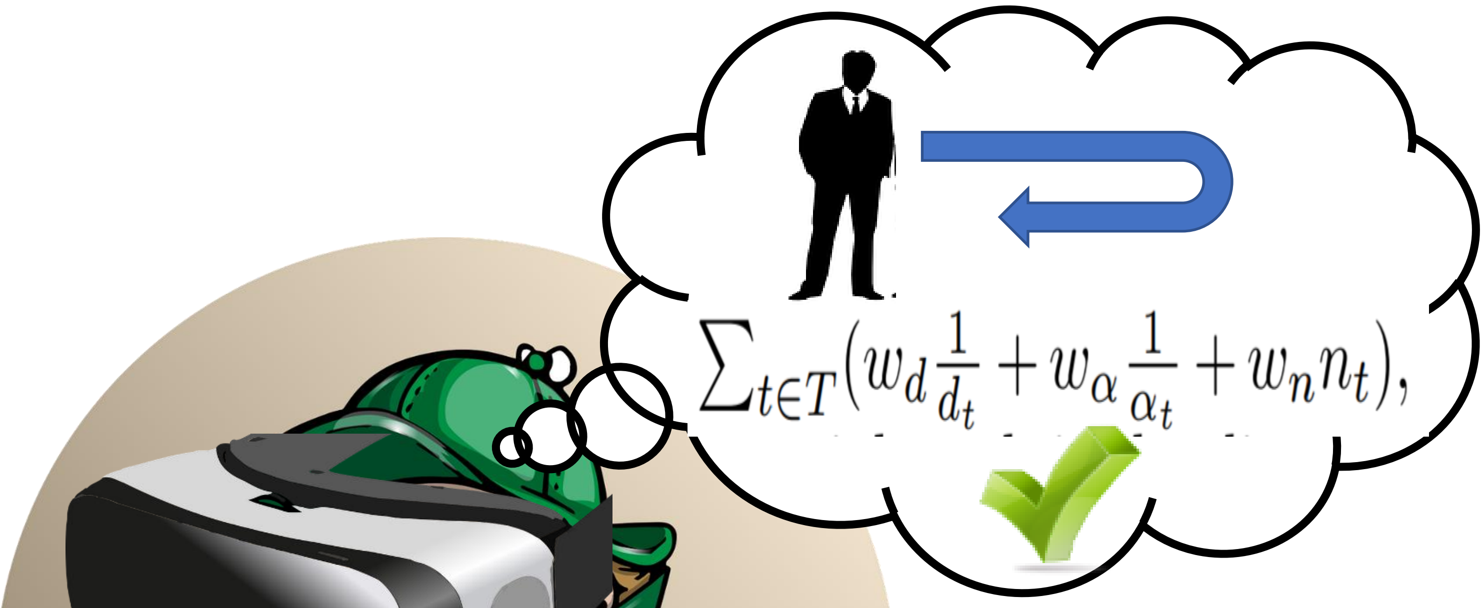
- Evaluate and compare different object identification methods that we implement within the tool
- Use datasets collected with the tool to demonstrate example uses

Let’s start with desert first …



$$\sum_{t\in T}\left(w_d\frac{1}{d_t}+w_\alpha\frac{1}{\alpha_t}+w_n n_t\right),$$

Back to the main meal …

How do we effectively identify and get info about visible objects?

Per-object vs constant-ray …

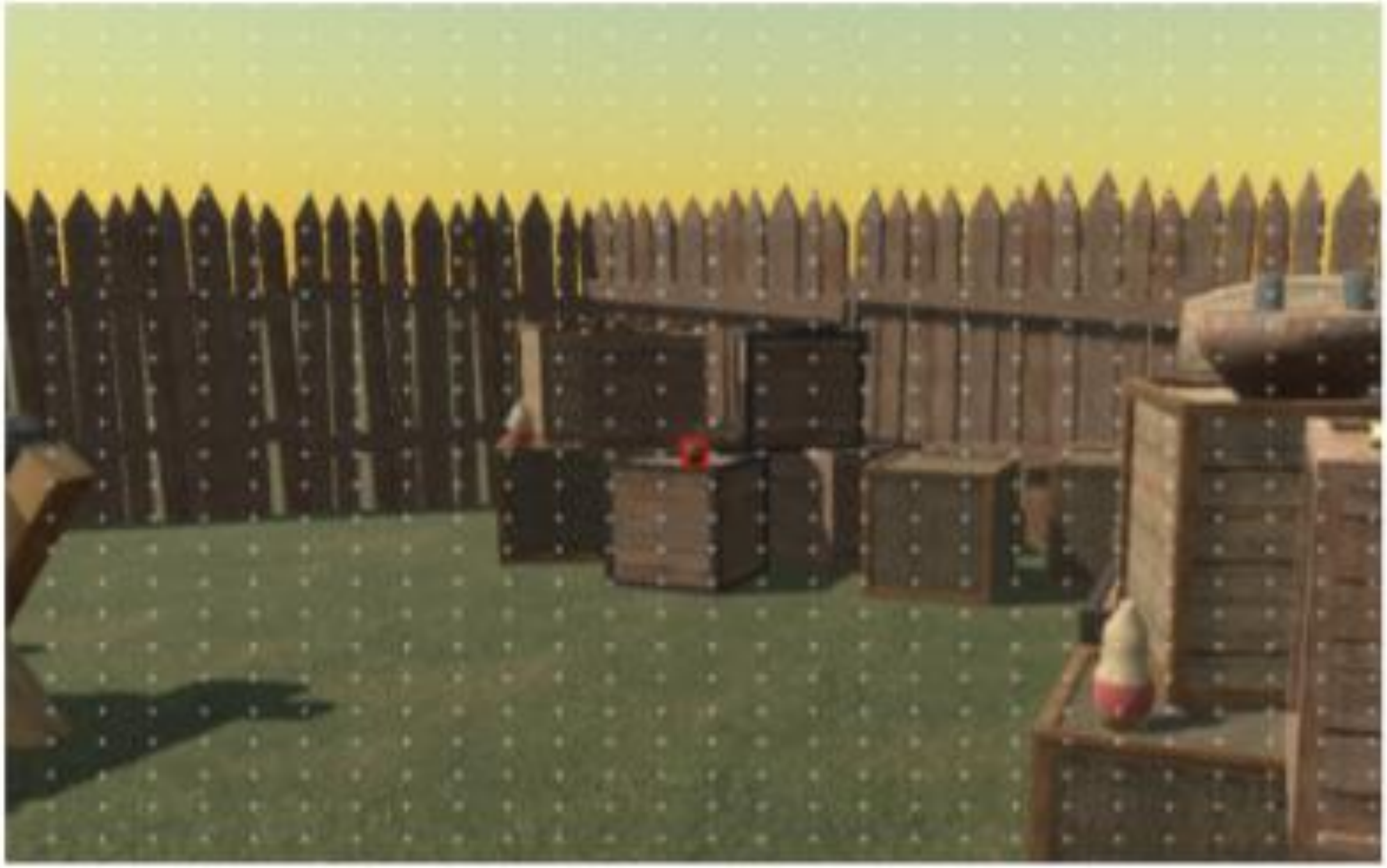
- Per-object does not scale well to large environments
  - Need to bound number of objects to consider

Per-object vs constant-ray ...

- Per-object approach does not scale well to large environments
  - Need to bound number of objects to consider

- Constant-ray approach considered next ...

Naïve ray-casting …

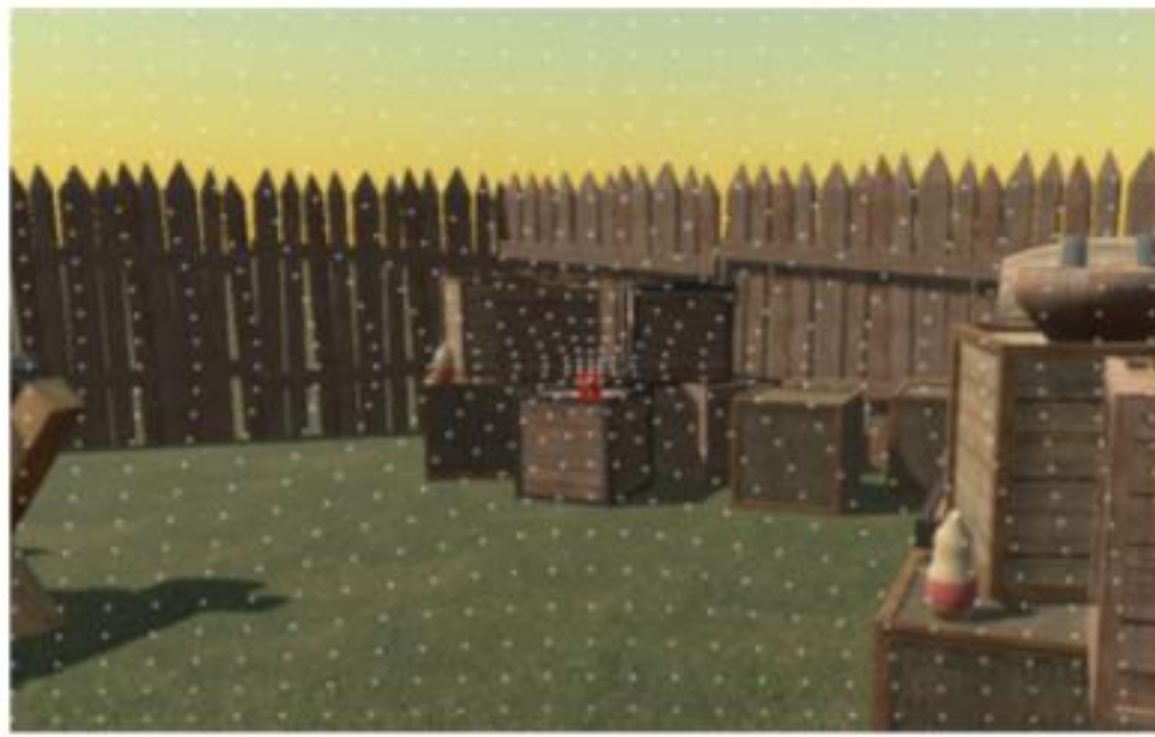


- Uniform grid …

Here, 1700 rays.

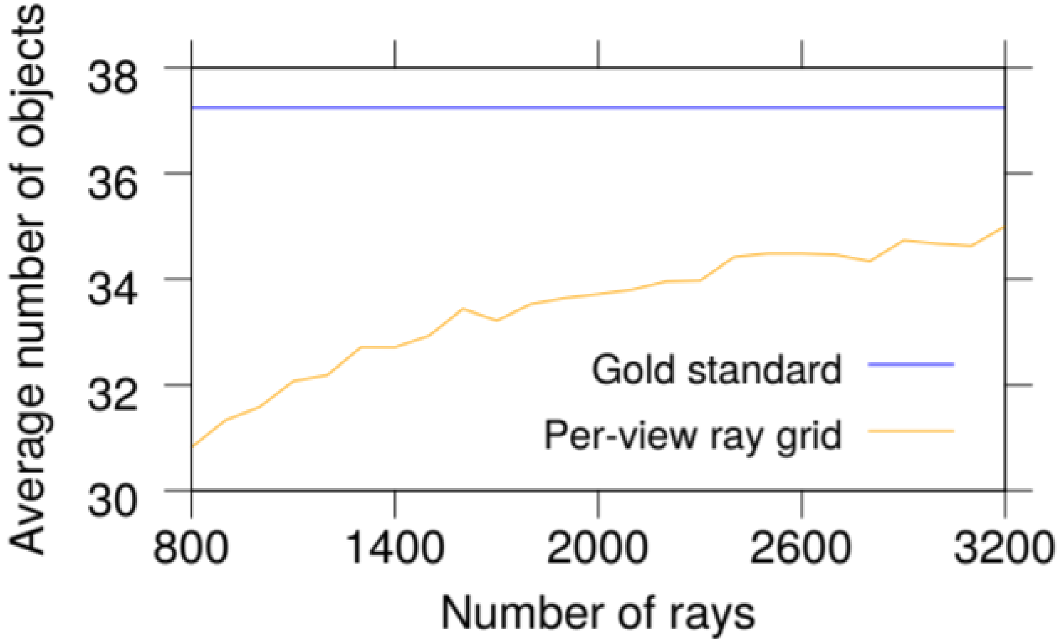
Baseline: Gaussian ray-casting …

$$f(x,y) = A \cdot e^{-\left(\frac{(x-x_0)^2}{2\cdot\sigma_x^2} + \frac{(y-y_0)^2}{2\cdot\sigma_y^2}\right)}$$



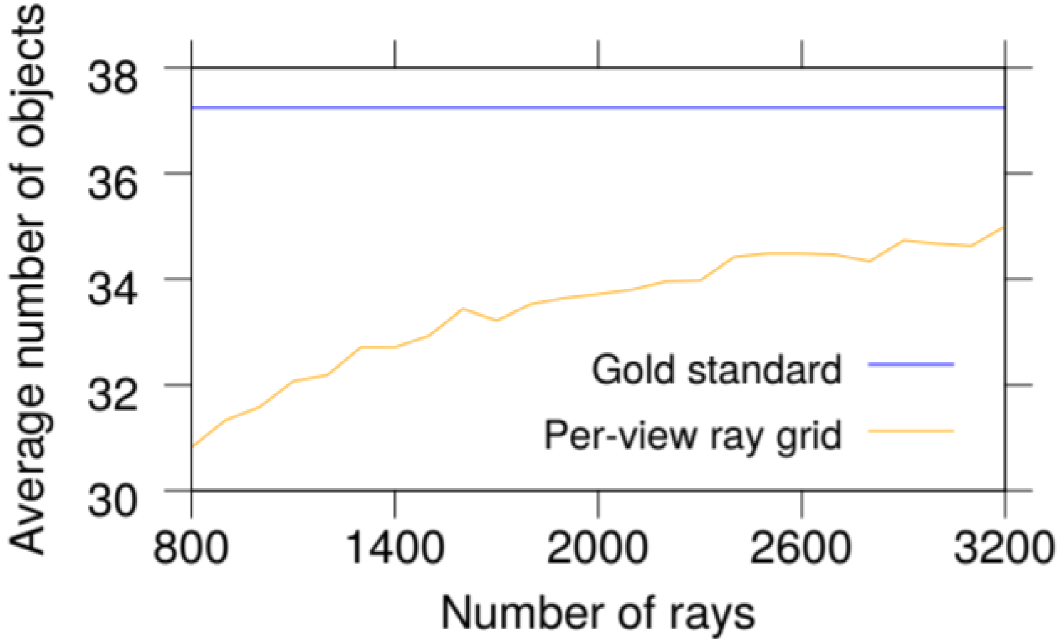
- More rays in center …

Evaluation: vs “gold standard”



- Diminishing returns

Evaluation: vs “gold standard”



- Diminishing returns
- With 3,200 rays, we miss only 7% of optimal

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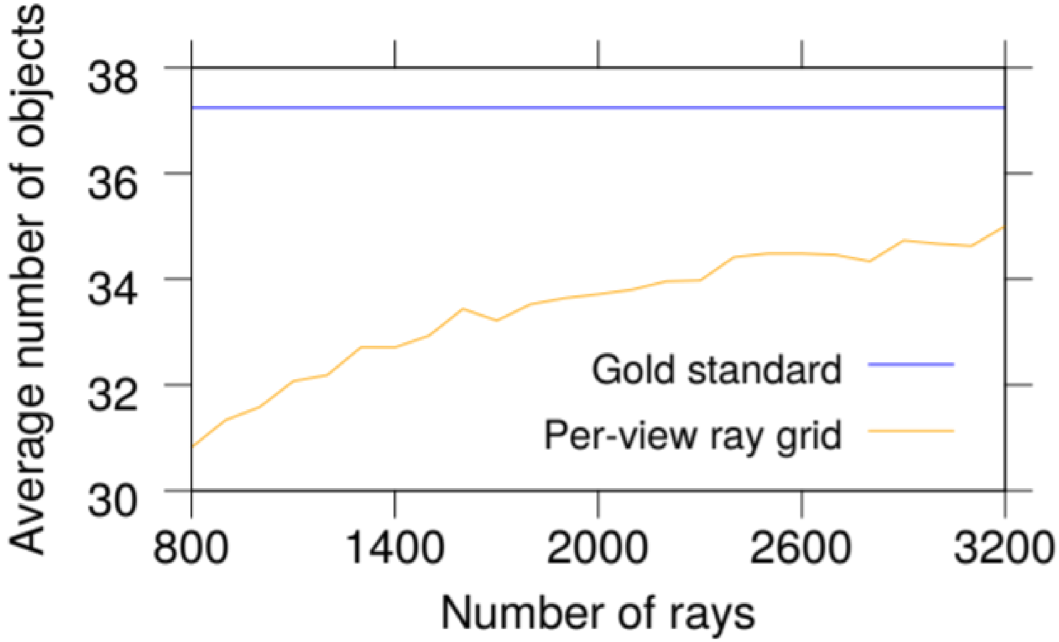

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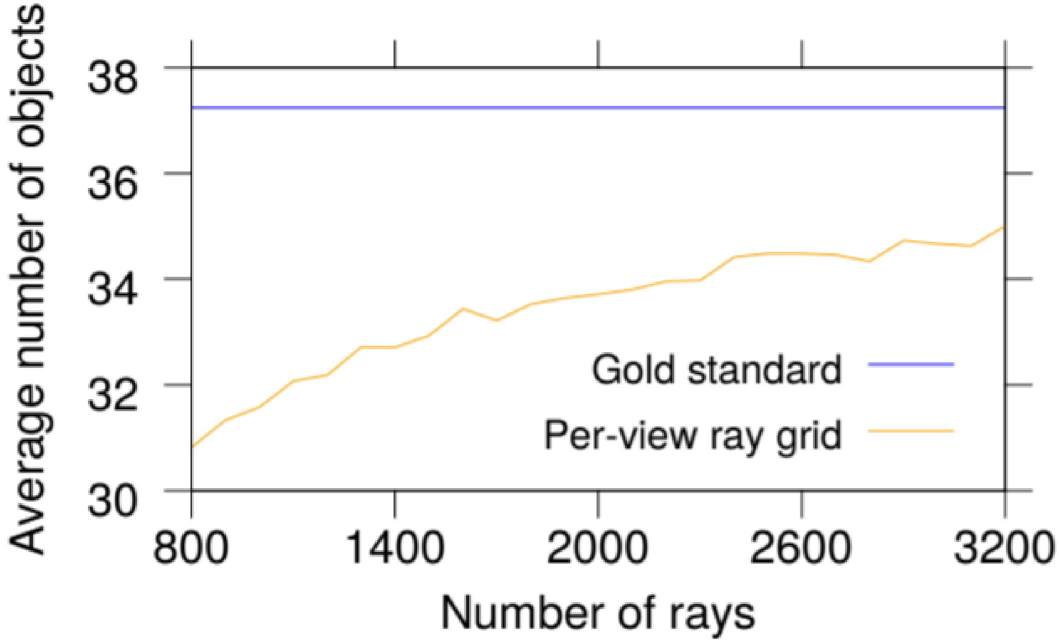

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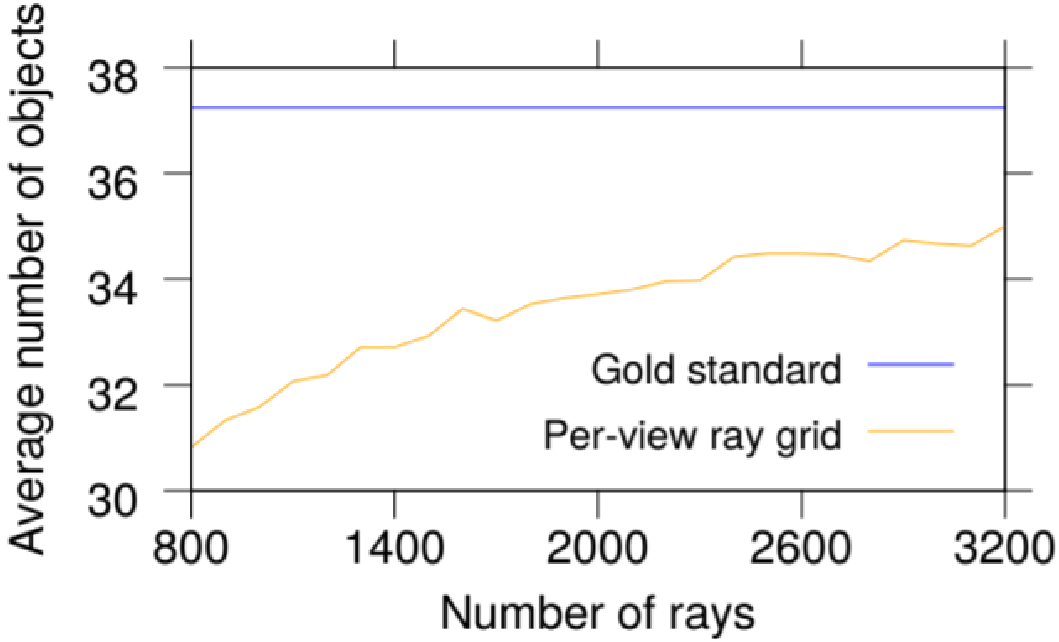

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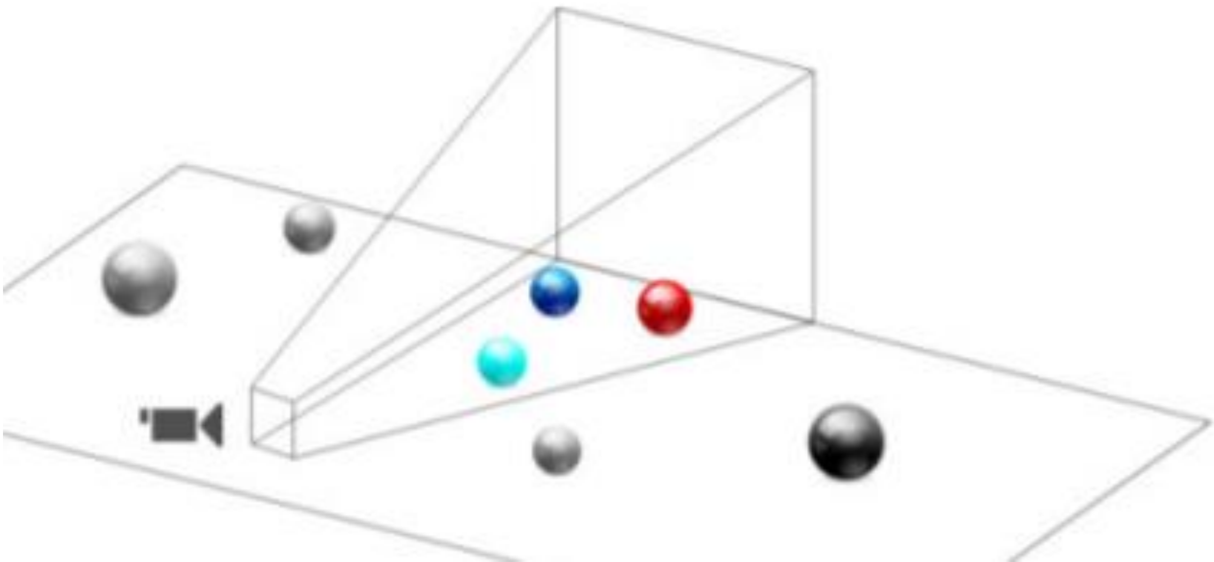
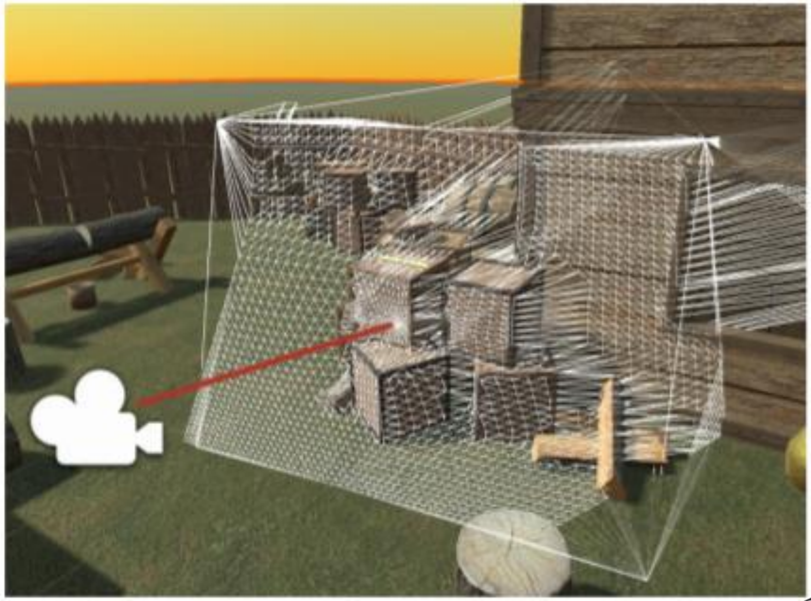
  - Every pixel covered and have not found any object that other methods observe that “gold standard” does not.
  - For this reason, later we will only report recall. (Precision is always 100%.)

Refinement methods

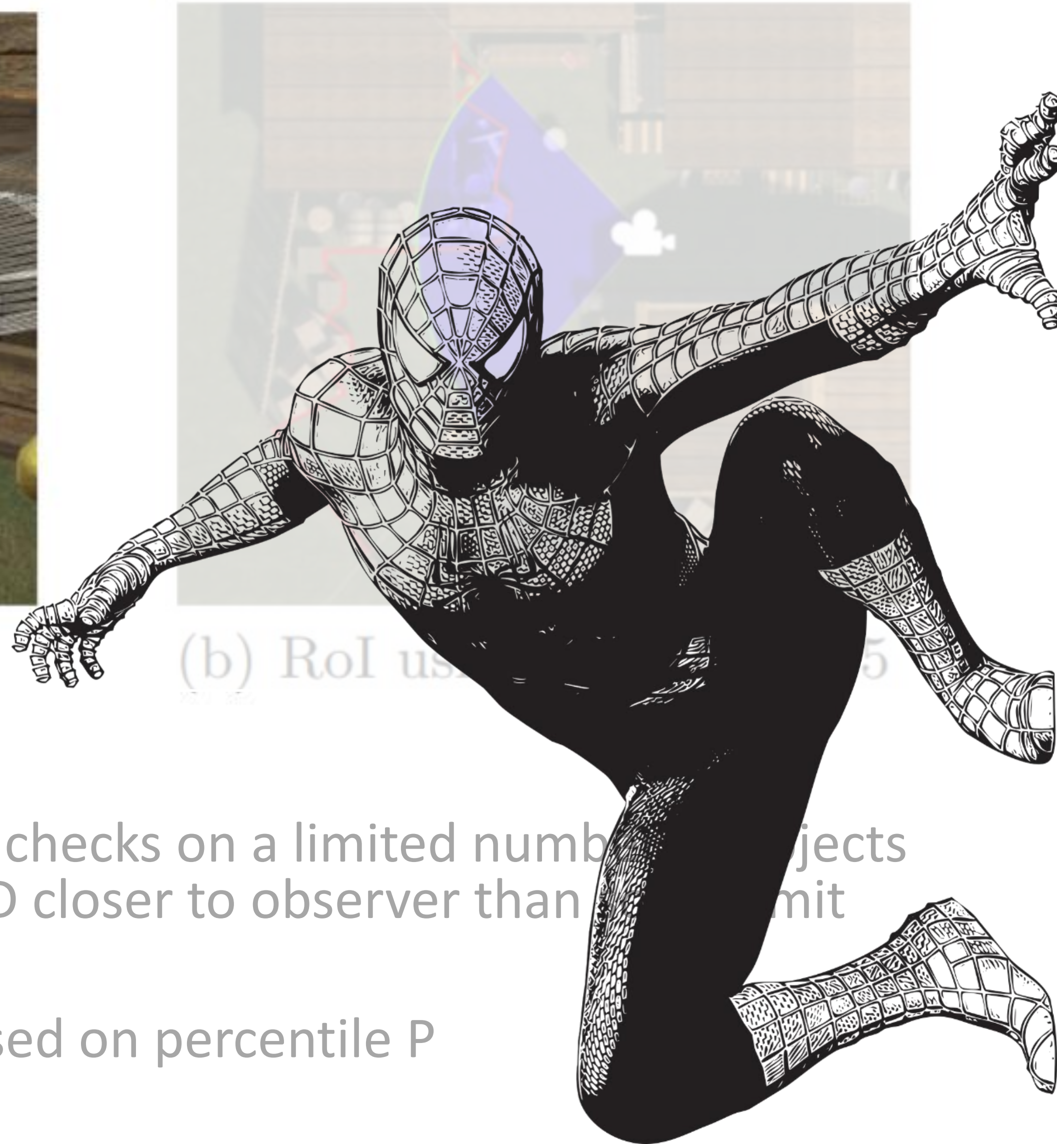


- Ideal: Perform extra per-object checks on a limited number of objects within the viewing frustum AND closer to observer than some limit

Refinement methods



(a) 3D Delaunay surface



(b) RoI us 5

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  - Delaunay surface (DS)
  - Distance threshold (DT) based on percentile P

Refinement methods

(a) 3D Delaunay surface

(b) RoI using DT, $P = 0.5$

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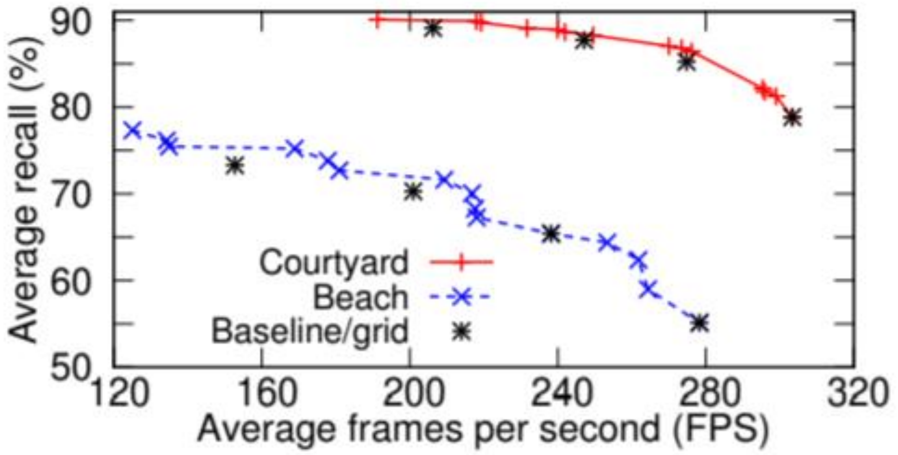
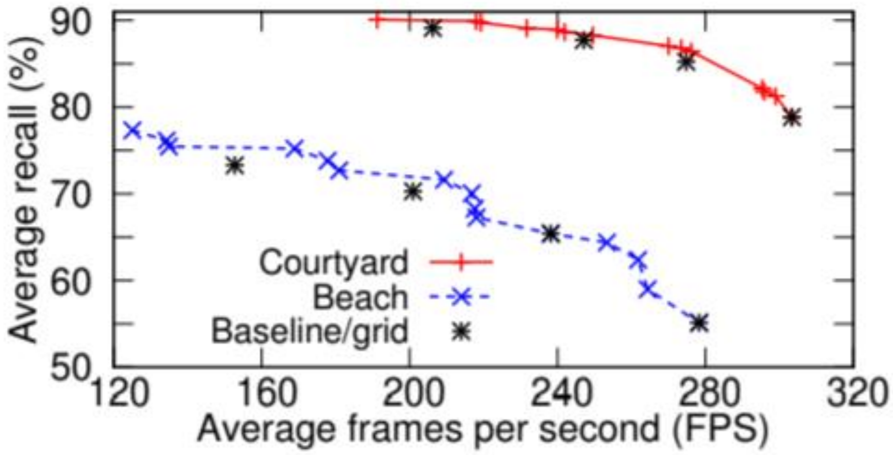
Example results



- Tradeoff between FPS and average recall

Example results



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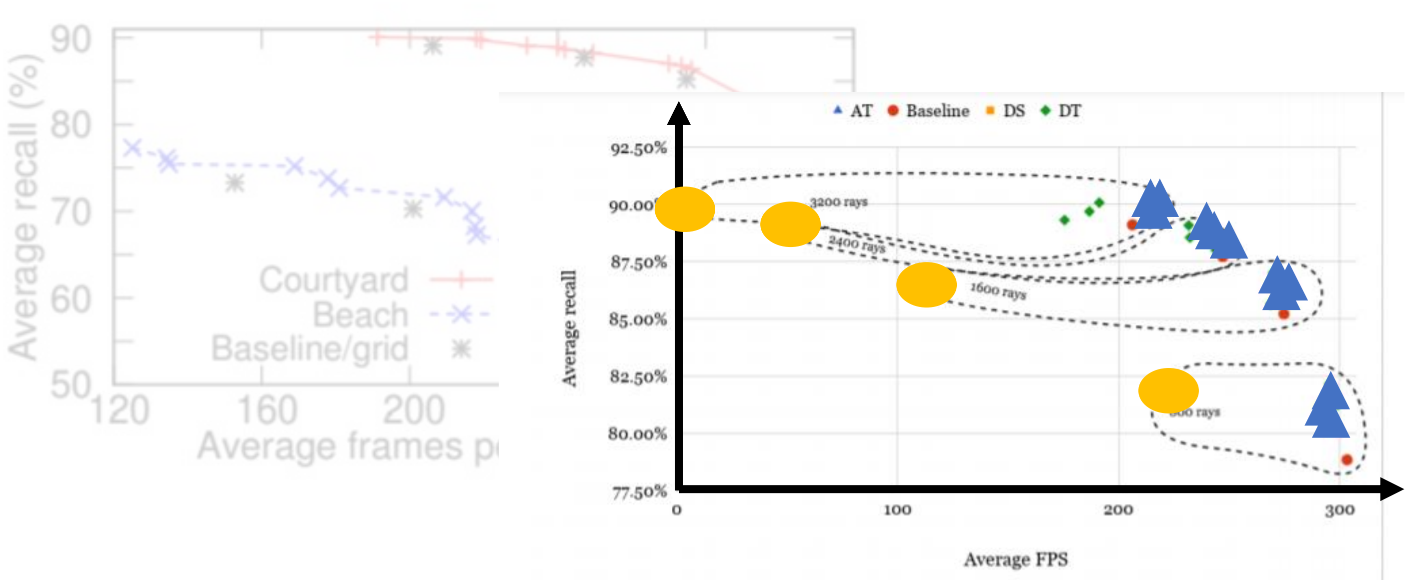
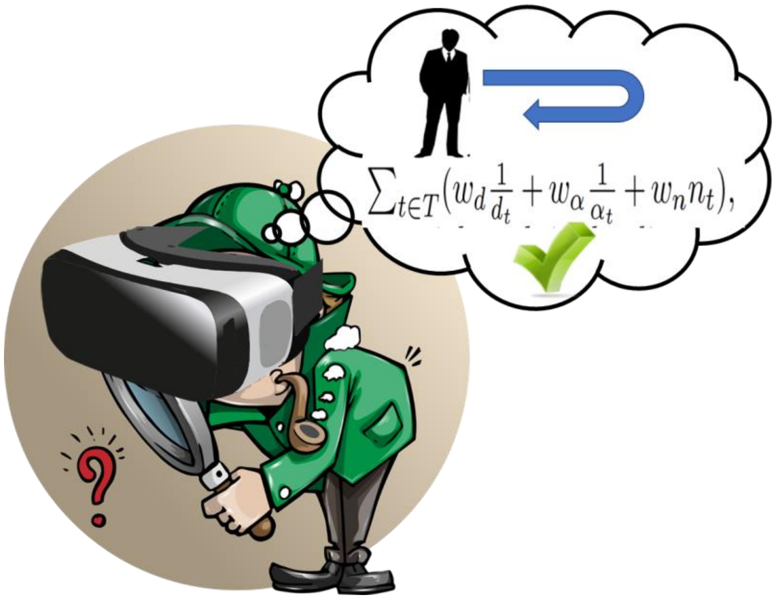


- Tradeoff between FPS and average recall
- Refinement methods can improve somewhat over baseline
  - Substantial overhead penalty to DS
  - DT typically provides the best tradeoff

Summary and conclusions

Methodology and software tool capturing

- **user movements** (position, rotation) and
- **visible objects** (object's identifier, distance, angle offset, volume, and how many rays hit the object at each time instance)
- at a **tunable time granularity** in immersive 3D environments.



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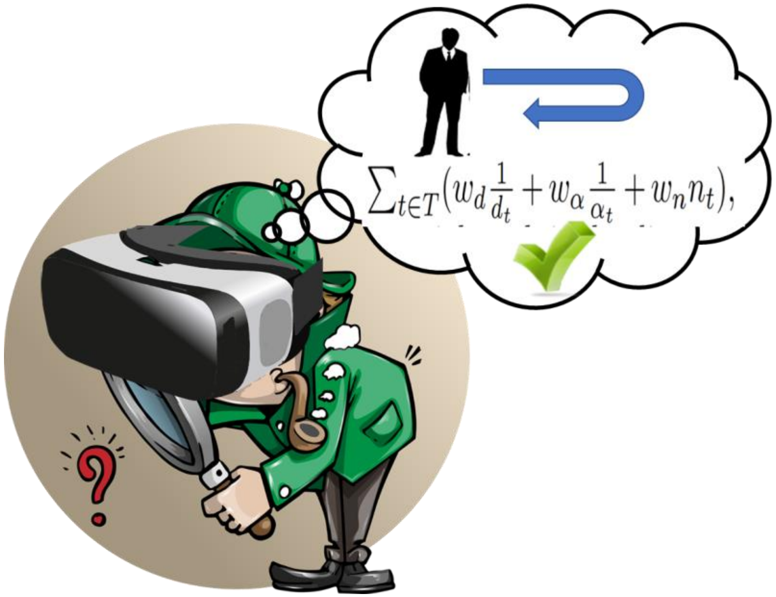
Lightweight object identification methods



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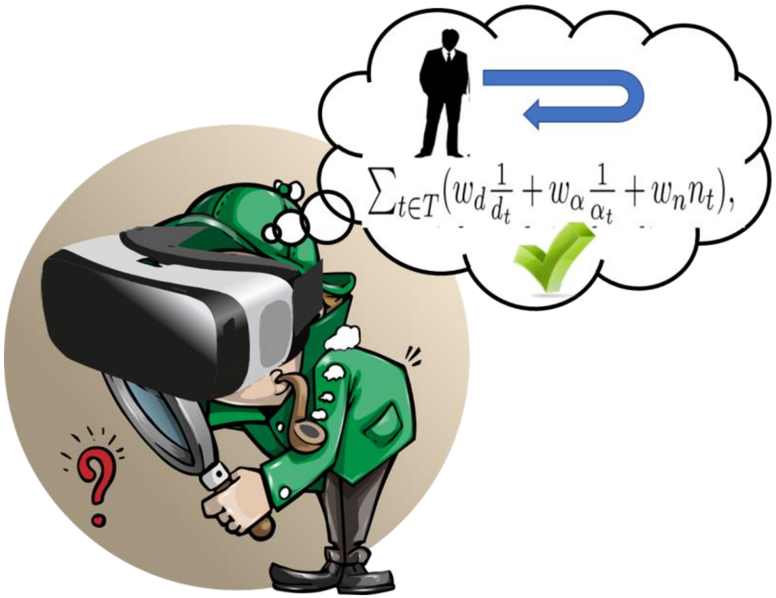
Relatively simple methods to illustrate example use cases



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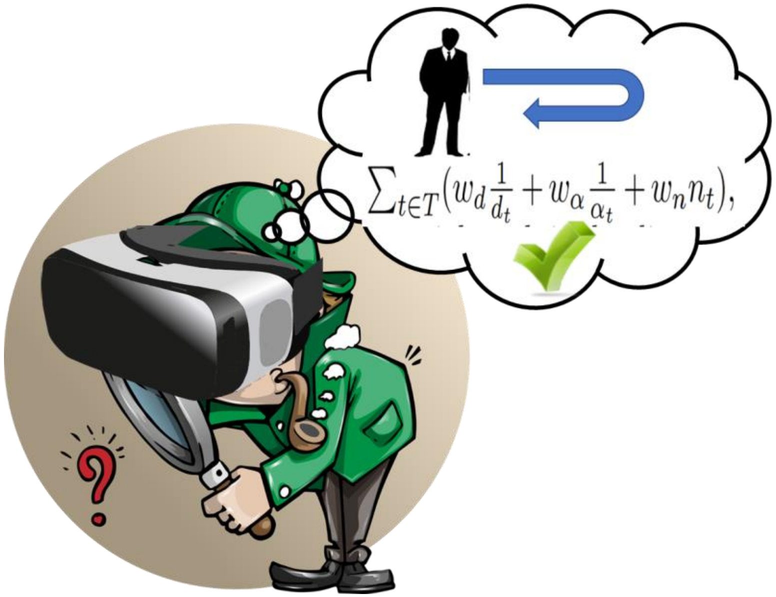

Future work include user studies

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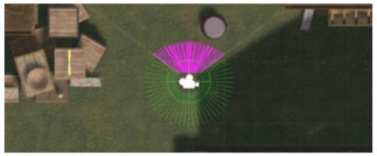
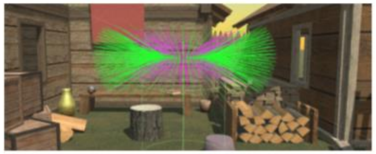
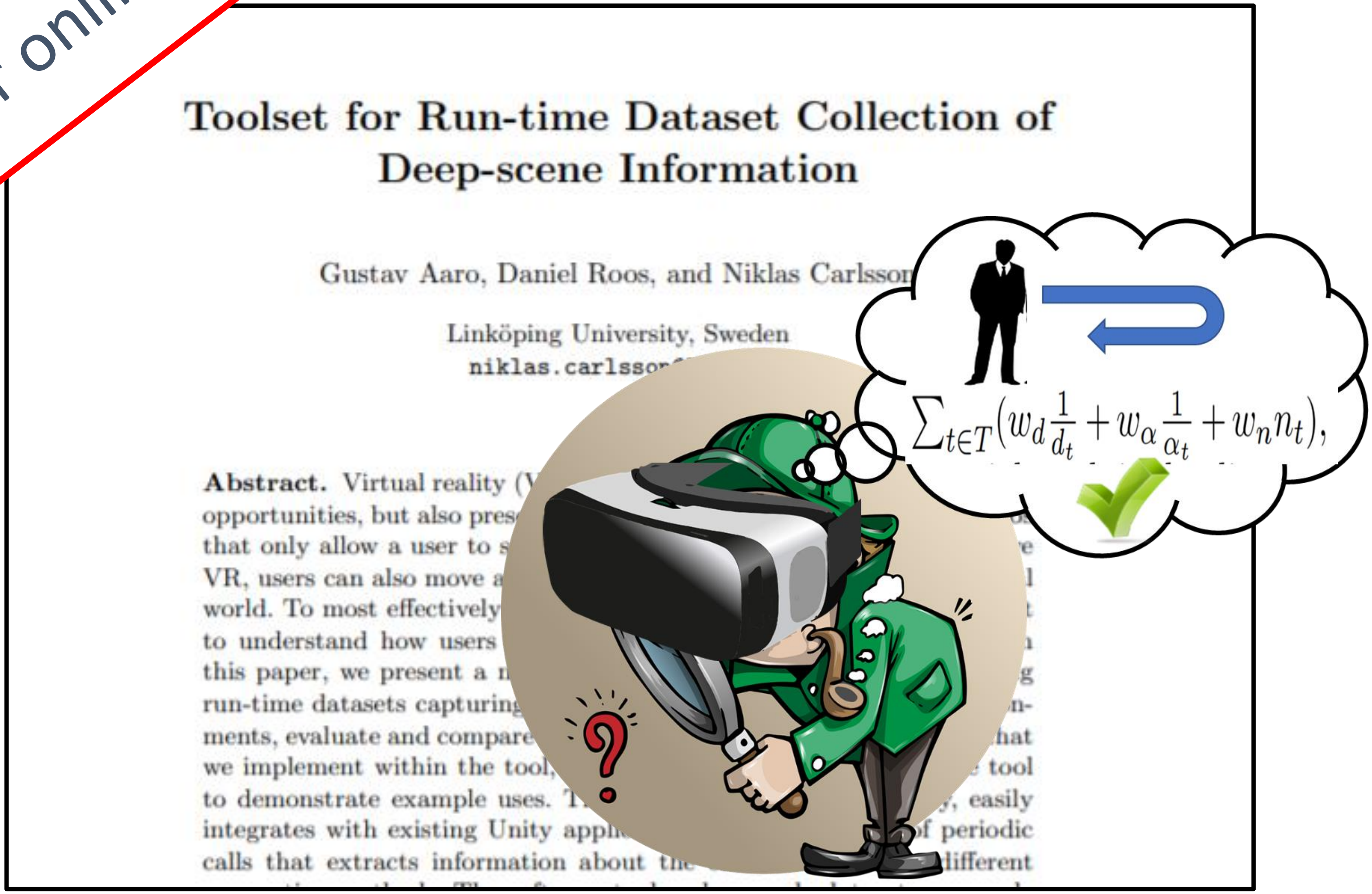
Future work include user studies

Have also extended tool to captures objects in other directions





Paper online!


Toolset for Run-time Dataset Collection of Deep-scene Information

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Linköping University, Sweden
niklas.carlsson

Abstract. Virtual reality (V
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that only allow a user to s
VR, users can also move a
world. To most effectively
to understand how users
this paper, we present a n
run-time datasets capturing
ments, evaluate and compare
we implement within the tool,
to demonstrate example uses. T
integrates with existing Unity appl
calls that extracts information about the

LINKÖPING UNIVERSITY

Niklas Carlsson (niklas.carlsson@liu.se)

* Illustrative images created using images from pixabay.com