Neural scene representation and rendering

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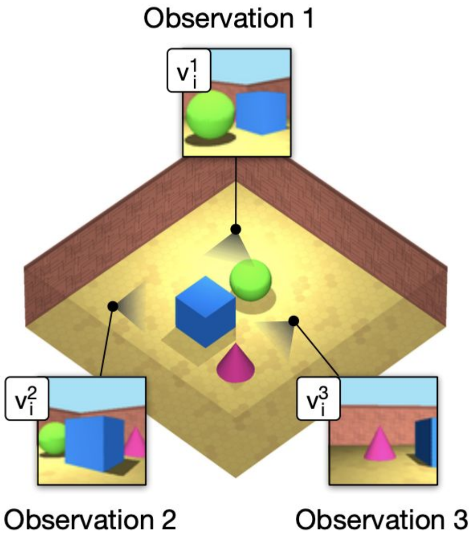
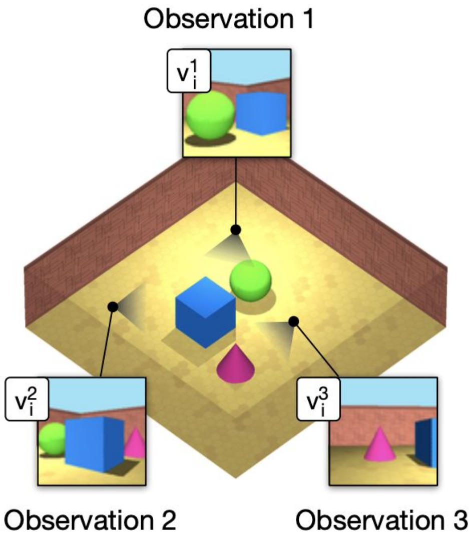
Motivation

- Humans can guess how an object looks like from perspectives that we have not seen.
  - Such visual and cognitive tasks are effortless to humans, but artificial systems are hardly capable of doing them
  - Most today's visual recognition systems are trained using large datasets (with annotated labels), which limits their capability.
  - We want machines that can automatically and fully understand the surroundings (objects, their attributes, light source, etc.) without manually giving data.



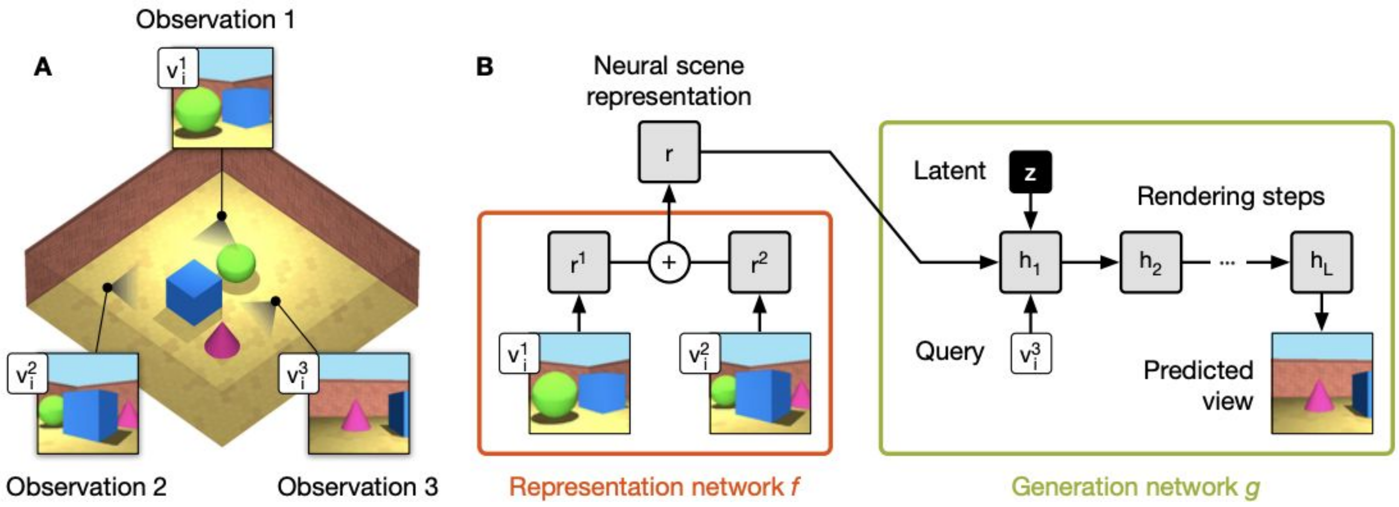
Task

- Scene Understanding
  - Many attributes in the scene (such as wall color, texture, multiple objects, their different sizes and colors)
  - If possible to imagine how different scenes looks like (answer) from a different point (query) based on previous observations (context), we can say the model understands the scene (as in a QA task in NLU)
  - We call this model Generative Query Network (GQN)



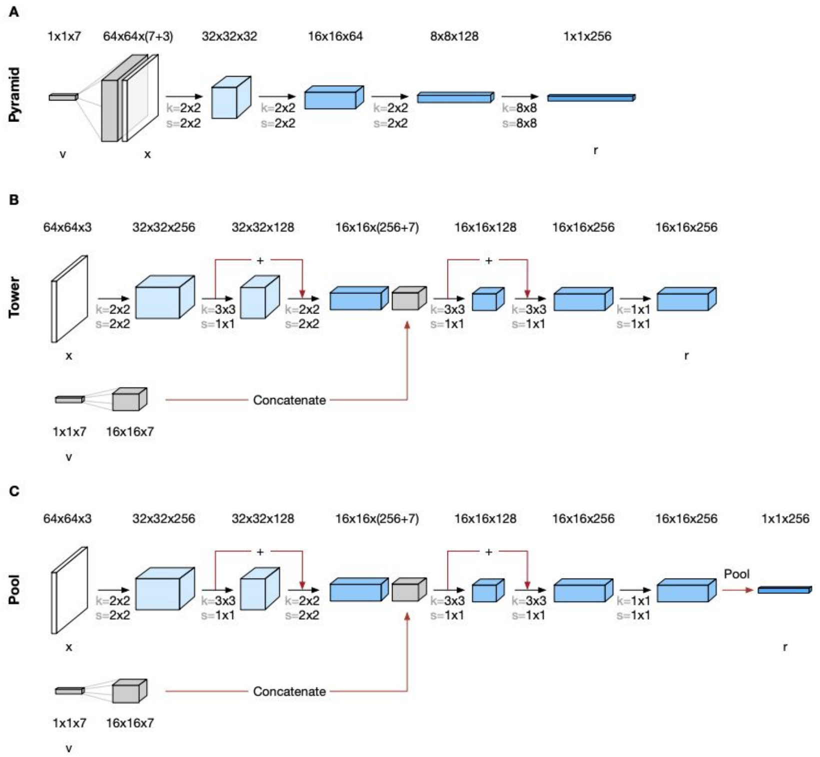
Model Architecture

- GQN has two networks: Representation network and Generative network



Model Architecture

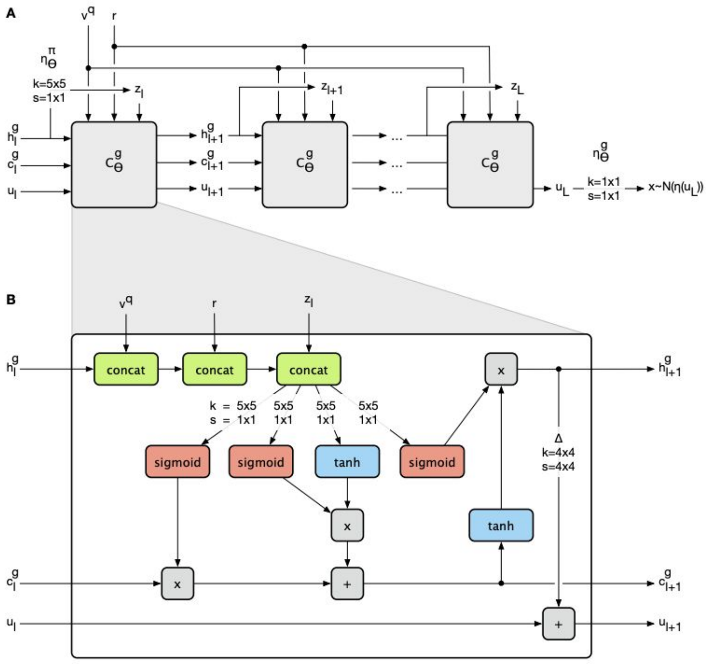
- Representation network
  - Input: $\boldsymbol{o}_i = \{(\boldsymbol{x}_i^k, \boldsymbol{v}_i^k)\}_{k=1,\ldots,K}$
  - Output: $\boldsymbol{r} = f_\theta(\boldsymbol{o}_i)$
  - If multiple r, we sum them
- Different characteristics for each network architecture:
  - Tower: fastest to learn, but less factorized
  - Pyramid & Pool: factorized across different object properties



Possible architectures

Model Architecture

- Generation network
  - Input: Query viewpoint, $\mathbf{v}^q$, and representation *r*
  - Output: Query image, $\mathbf{x}^q$
- Recurrent latent variable model (RNN + VAE)
  - Vector of latent variable *z* is split into *L* groups in an auto-regressive manner
  - Latent variable for each *l*: $\pi_\theta(\mathbf{z}_l|\mathbf{v}^q, \mathbf{r}, \mathbf{z}_{<l}) = \mathcal{N}(\mathbf{z}_l|\eta^\pi_\theta(h^g_l)),$
  - The prior: $$\pi_\theta(\mathbf{z}|\mathbf{v}^q, \mathbf{r}) = \prod_{l=1}^{L} \pi_\theta(\mathbf{z}_l|\mathbf{v}^q, \mathbf{r}, \mathbf{z}_{<l})$$



One possible architectures

Training

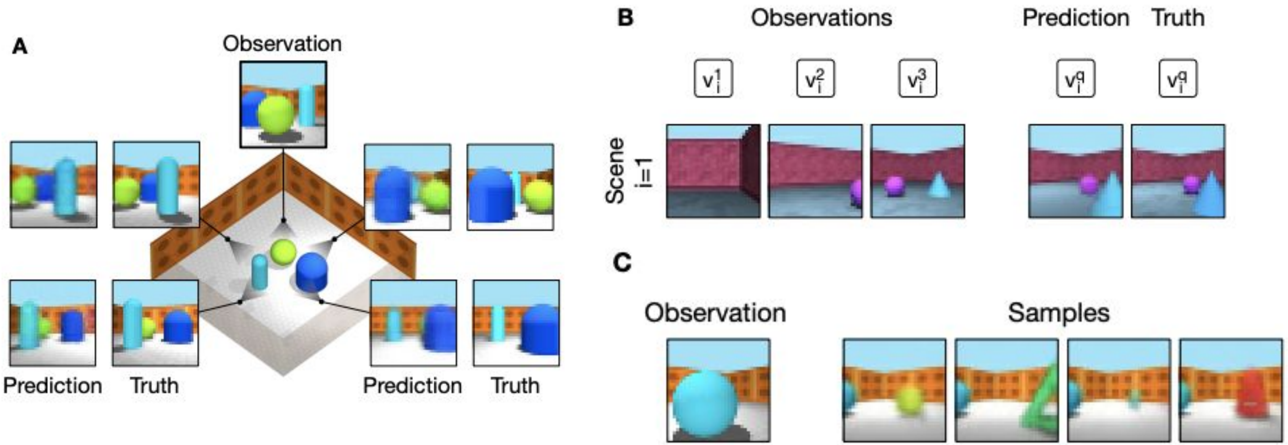
- Meta-learning style of training
  - For each iteration, we train on new different scenes, to avoid overfitting to one scene
  - Forced to learn whatever context the model gets

- Optimization
  - Variational approximation by minimizing the loss function below
  - Evidence lower bound (ELBO), here *-F(θ, φ)*, is decomposed into the reconstruction likelihood and a regularization term

$$\mathcal{F}(\theta, \phi) = \mathbb{E}_{(\mathbf{x},\mathbf{v})\sim D, \mathbf{z}\sim q_\phi} \left[-\ln \mathcal{N}\left(\mathbf{x}^q | \eta_\theta^g\left(\mathbf{u}_L\right)\right) + \sum_{l=1}^{L} \mathbf{KL}\left[\mathcal{N}\left(\cdot|\eta_\phi^q\left(\mathbf{h}_l^e\right)\right) || \mathcal{N}\left(\cdot|\eta_\theta^\pi\left(\mathbf{h}_l^g\right)\right)\right] \right]$$

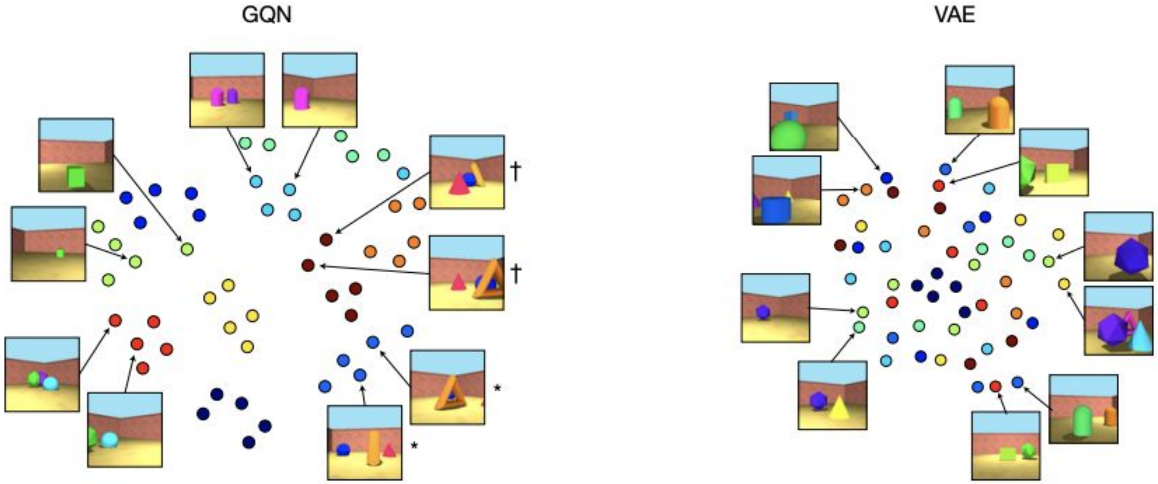
Experiments

- Neural scene representation and rendering
    - GQN's generator learns an approximate 3D renderer (a program that can generate an image when given a scene representation and camera viewpoint)
    - (A) Accurate images from arbitrary query viewpoint; (B) Consistent with laws of perspective, occlusion, and lighting; (C) Sample variability indicates uncertainty over scene contents



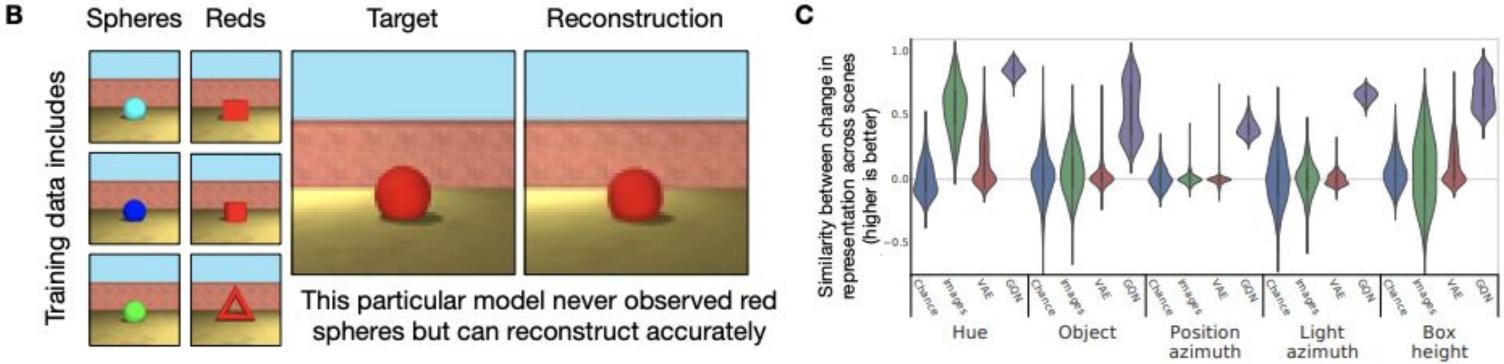
Experiments

- Viewpoint invariance
  - t-SNE embeddings visualization (GQN vs VAE)
  - VAE captures mostly wall angles; GQN can encode scene representations computed from each image individually



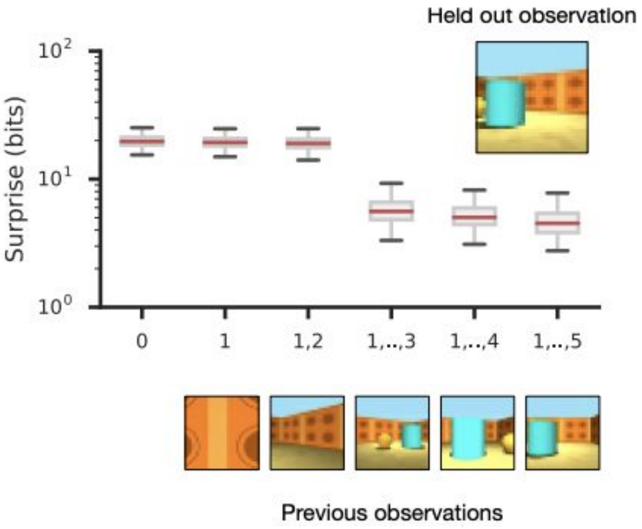
Experiments

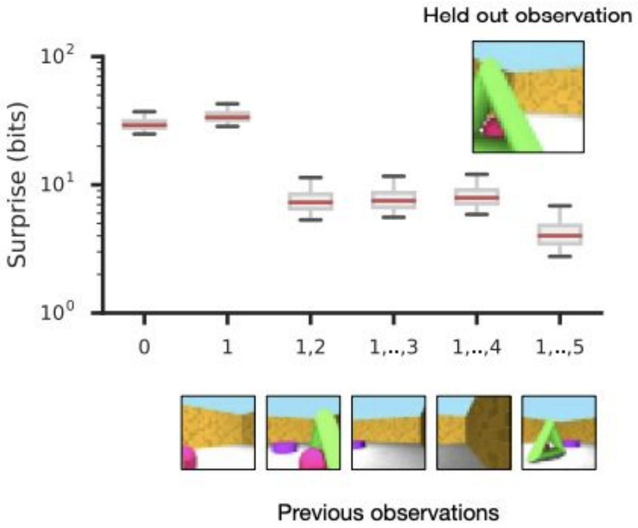
- Compositionality and factorization of the learned scene representations
  - (B) Reconstruction of holdout shape-color combinations.
  - (C) By changing one attribute, the representations are shifting (factorization of scenes representations)



Experiments

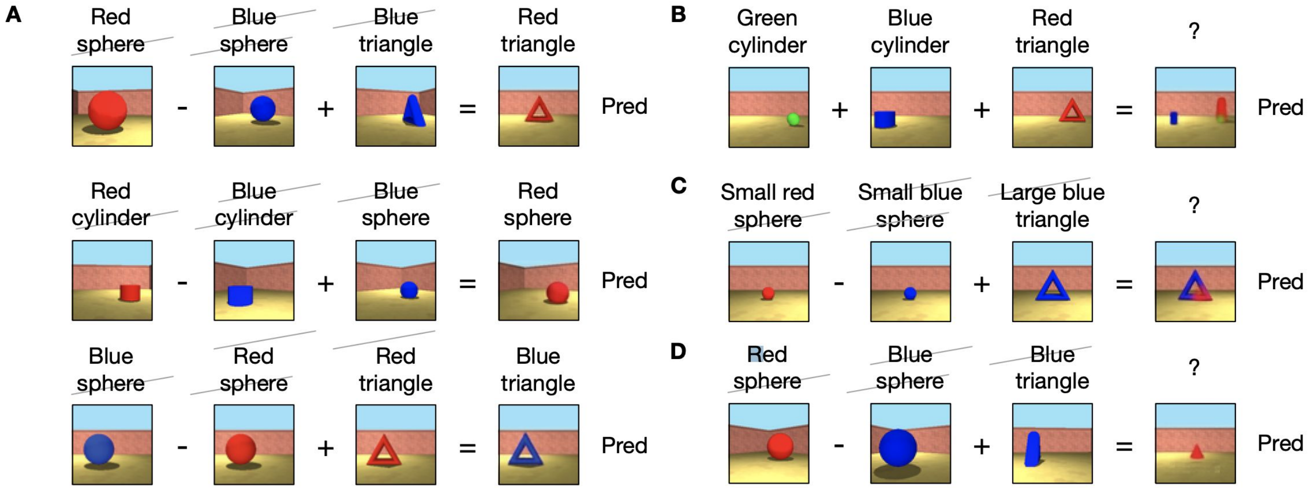
- Information gain
  - The model’s surprise of the held-out observation drops most sharply when it views the similar scenes (position, shape, color, etc.)



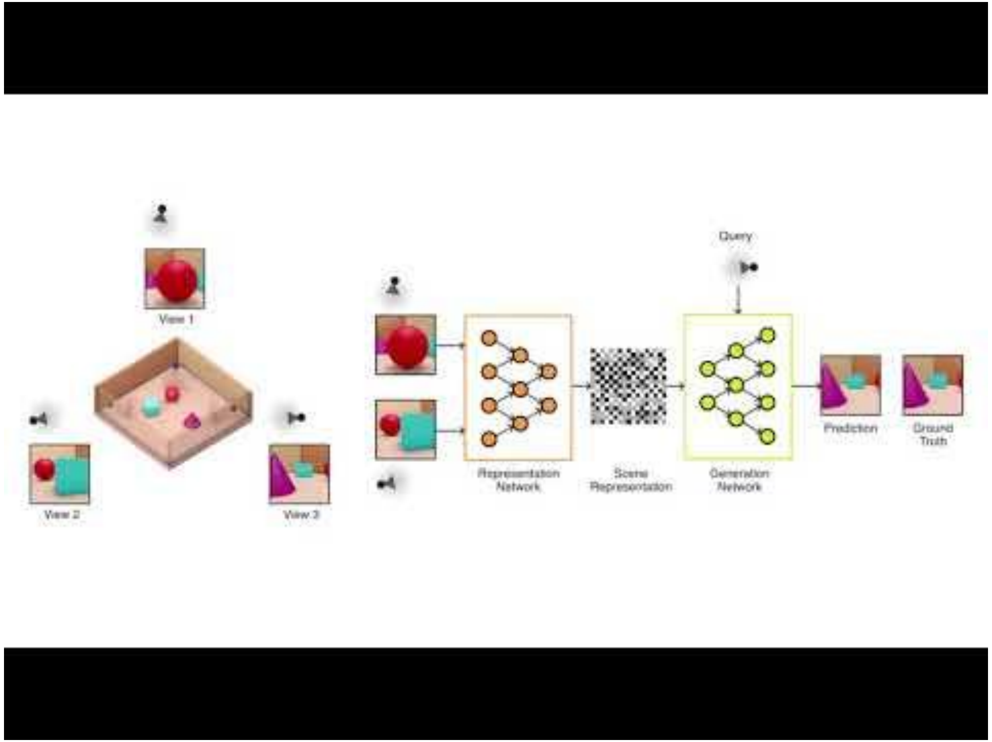


Experiments

- Scene algebra
  - The model can correctly modify/recombine scenes in a variety of settings
  - But fail to combine different objects in (B) and objects with different sizes in (C)



Summary


View 1
View 2
View 3
Query
Representation Network
Scene Representation
Generation Network
Prediction
Ground Truth

Related Work

- Traditional structure-from-motion, structure-from-depth and multi view geometry techniques
    - Requires 3D structure of the environment
- Classical neural generative models (e.g. auto-encoding, density models)
    - Capturing only the distribution of observed images
- Viewpoint transformation networks
    - Requires explicit relationships; non-probabilistic and limited in scale

Contribution

- GQN learns representations that adapt to and compactly capture the important details of its environment (positions, color, objects, textures, lights, etc.) without any human labelling of the scenes
- GQN learns disentangled semantics (though not interpretable by humans) by itself and in a generally applicable manner
- GQN learns a powerful neural renderer that is capable of producing accurate and consistent images of scenes from new query viewpoints
- A step towards fully unsupervised scene understanding