AGA: Attribute-Guided Augmentation

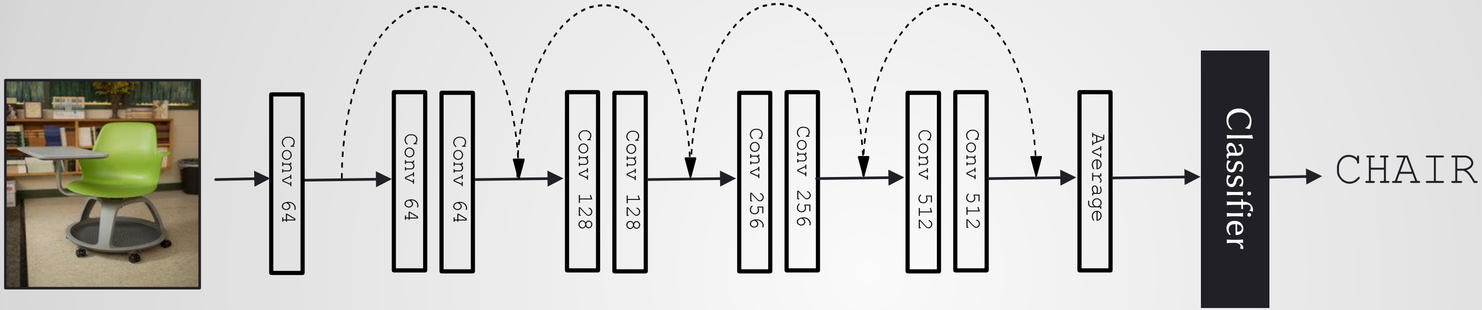
Mandar Dixit
UC San Diego

Roland Kwitt
University of Salzburg

Marc Niethammer
UNC Chapel Hill

Nuno Vasconcelos
UC San Diego

Visual Recognition



Convolutional Neural Networks (CNNs) + Large-scale datasets

Challenge(s): appearance, pose, location invariance

Data Augmentation

Augmentation in **IMAGE space**

Original

Flip

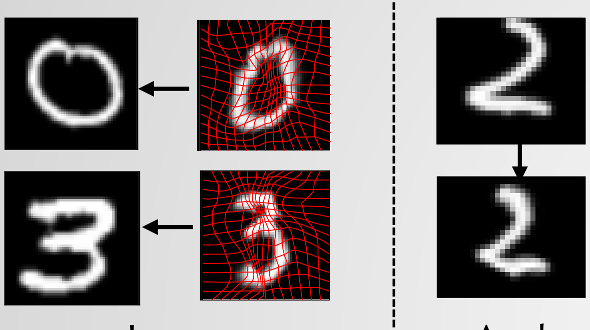
(Random) Crops

Crop + Flip

- Transformed copies of the original image
- Possible with simple image processing

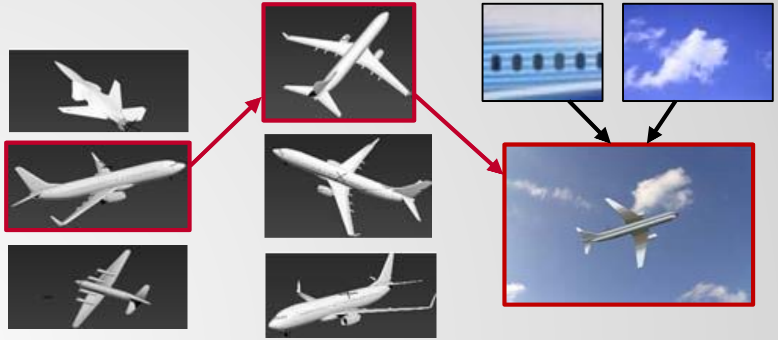
[Chatfield et al. 2014]
[Zeiler & Fergus 2014]
[Krishevsky et al. 2012]

Guided Data Augmentation



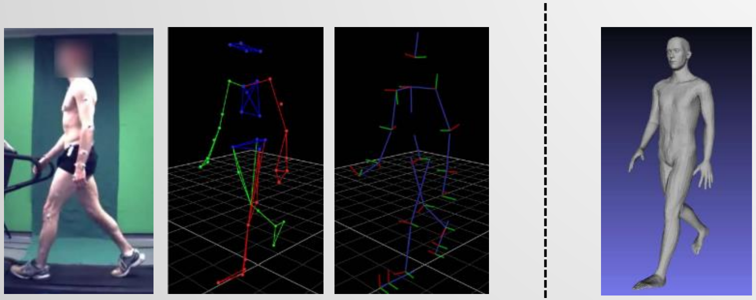
Learn Apply

[Hauberg et al. 2016]



3D CAD based rendering

[Peng et al. 2015]



3D Motion Capture Synthesize

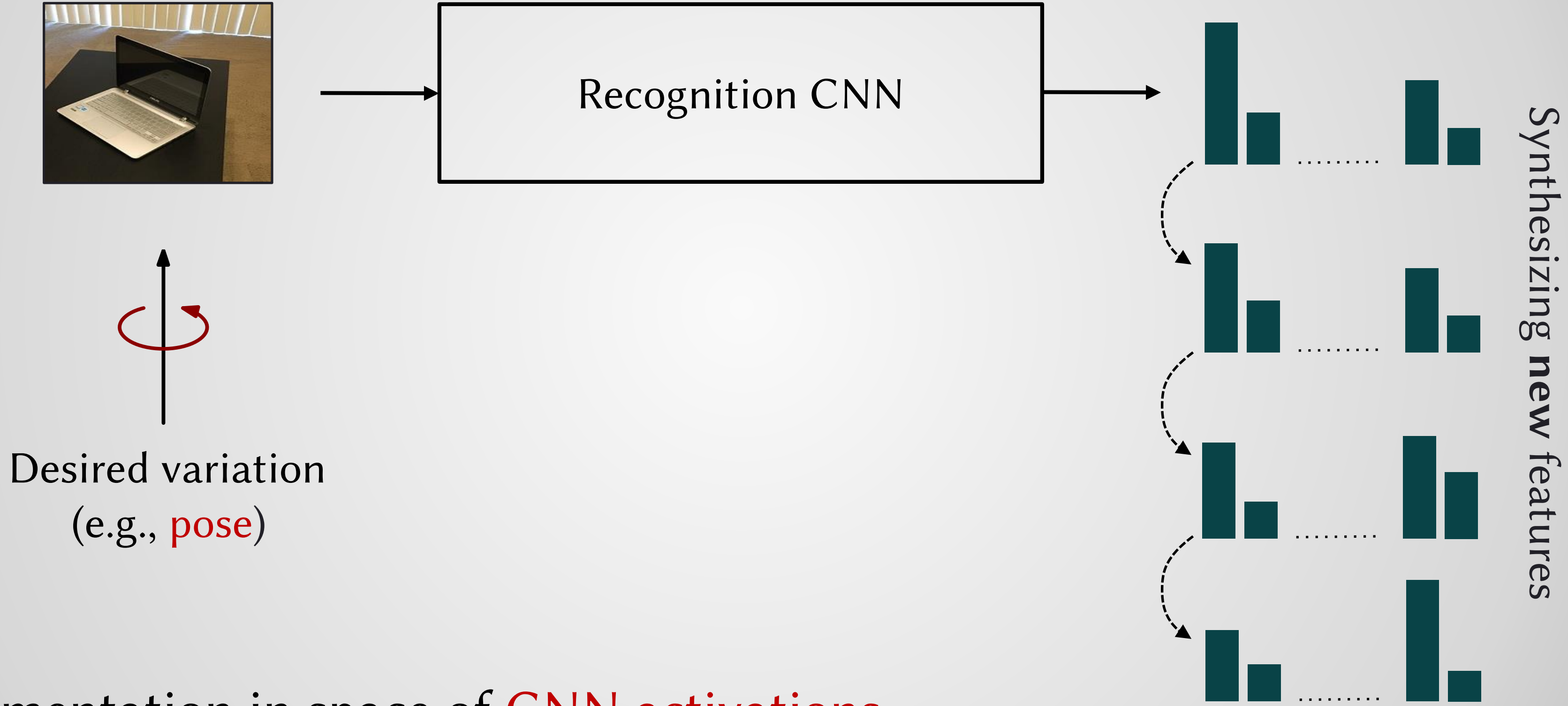
[Charalombous et. al. 2016], [Rogez & Schmid 2016]

Synthesis of *non-trivial* variations

- Either trivial in stimuli, e.g., digits
- Or require rendering from 3D

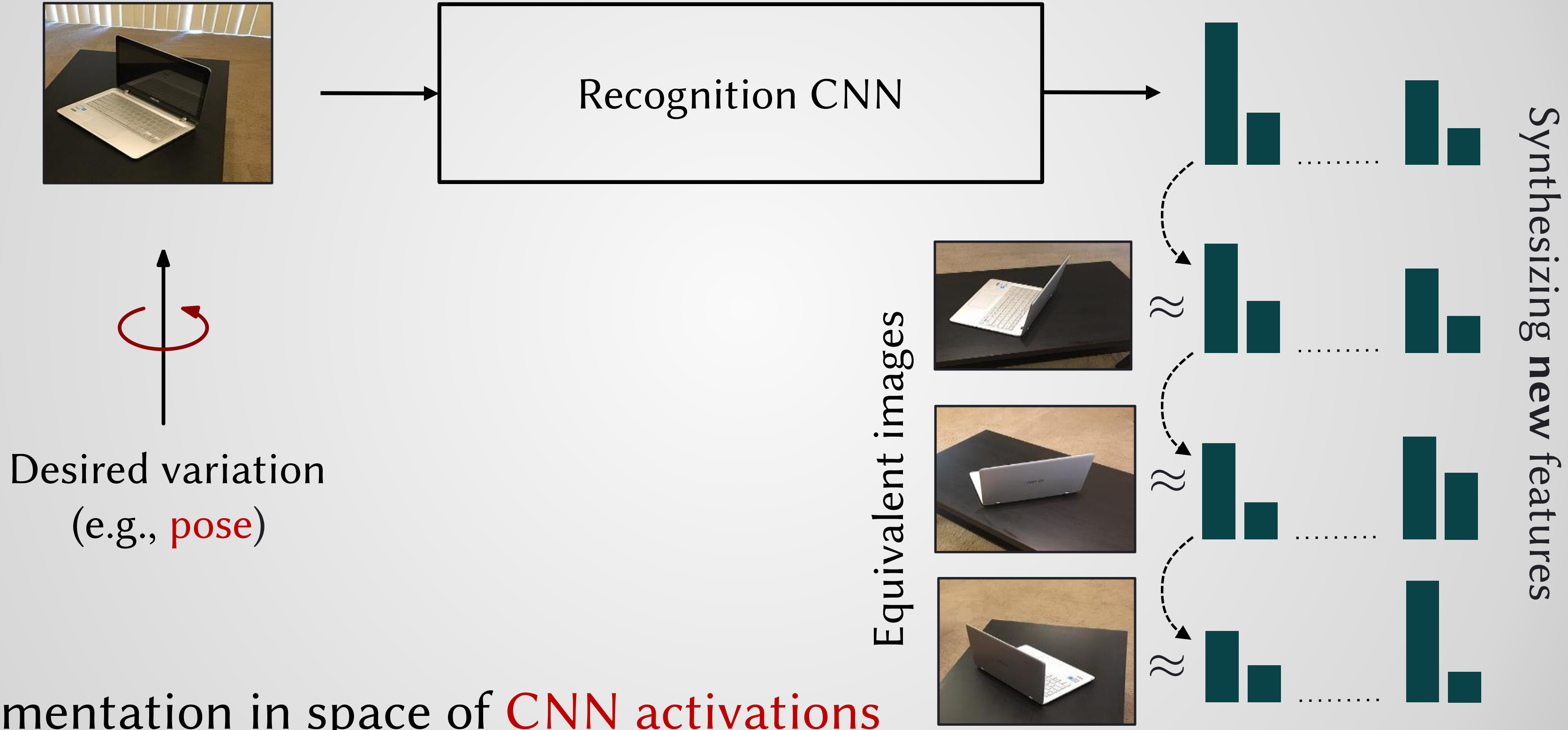
- Image space - high dimensional
- Learning needs lot of data

Objective



Augmentation in space of CNN activations

Objective



Augmentation in space of CNN activations

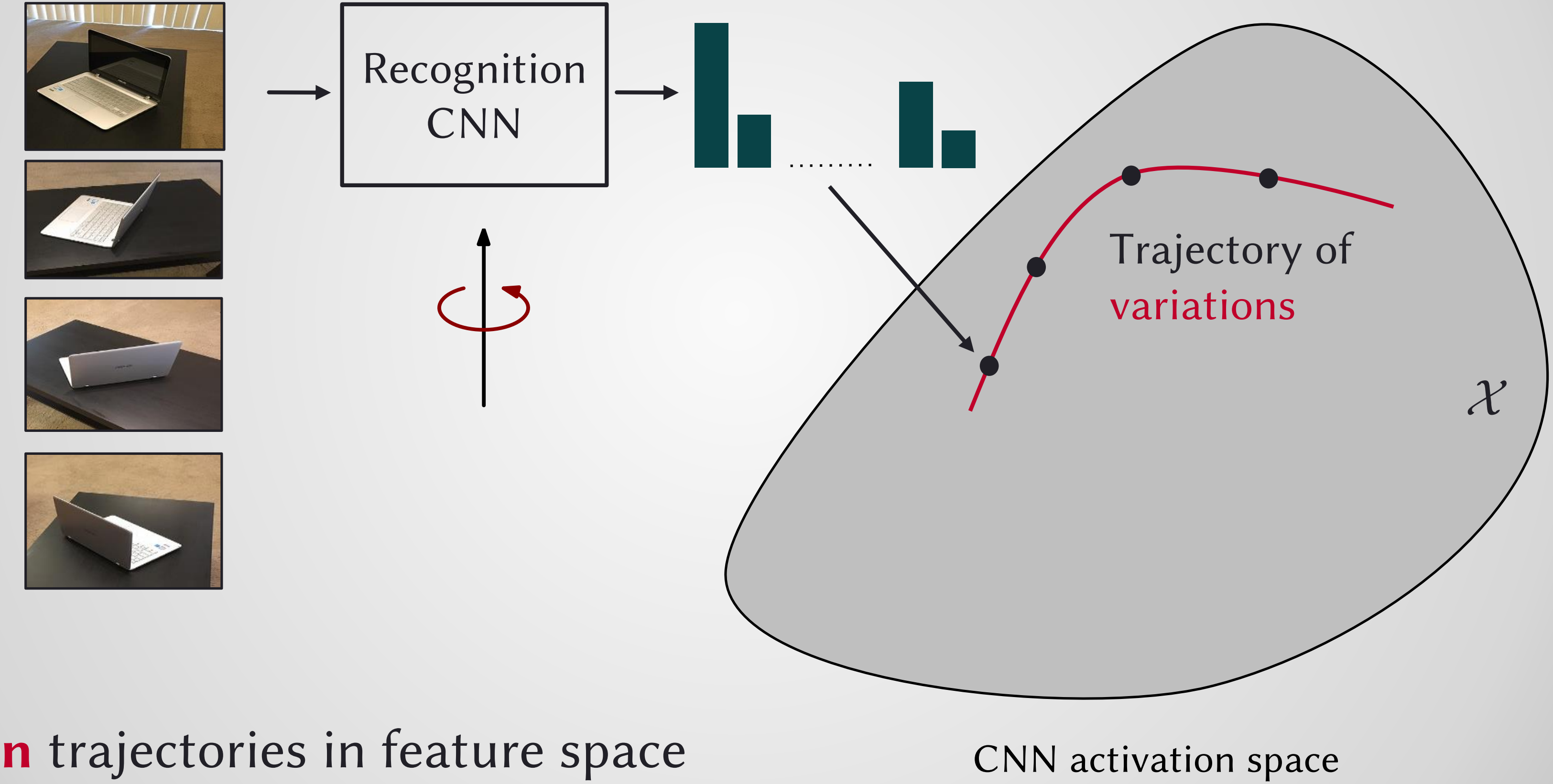
Data Augmentation

Augmentation in **FEATURE space**

- Inherits all the invariance of a CNN's representation
- Deep representations "unfold" the manifold of images [Bengio et al. 2012] (e.g., very recently leveraged in [Upchurch et al. 2016])
- Augmentation is performed in a space where trajectories of variation are "easier" to learn (e.g., with less data)

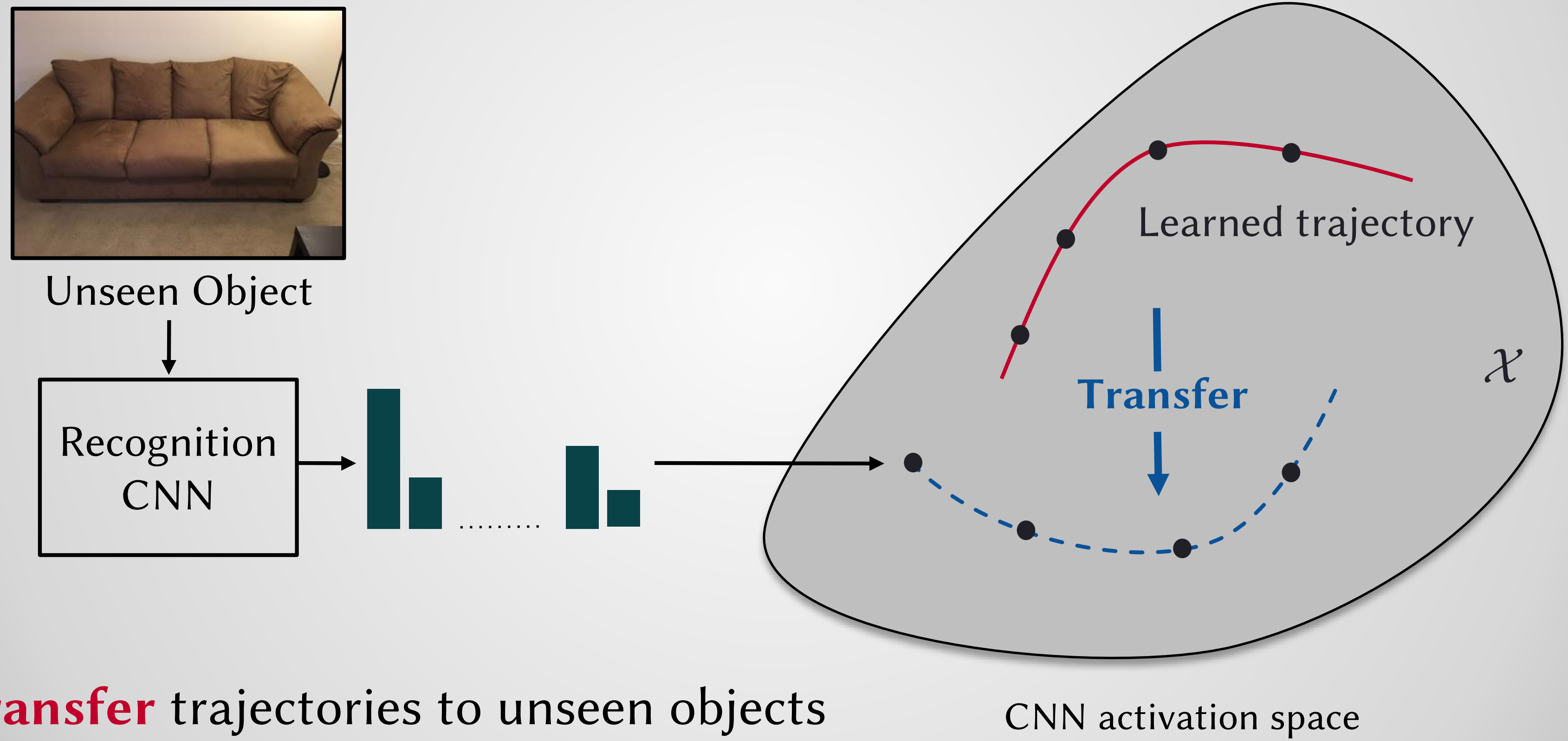
This is the strategy we advocate in this work!

A Regression / Synthesis Problem



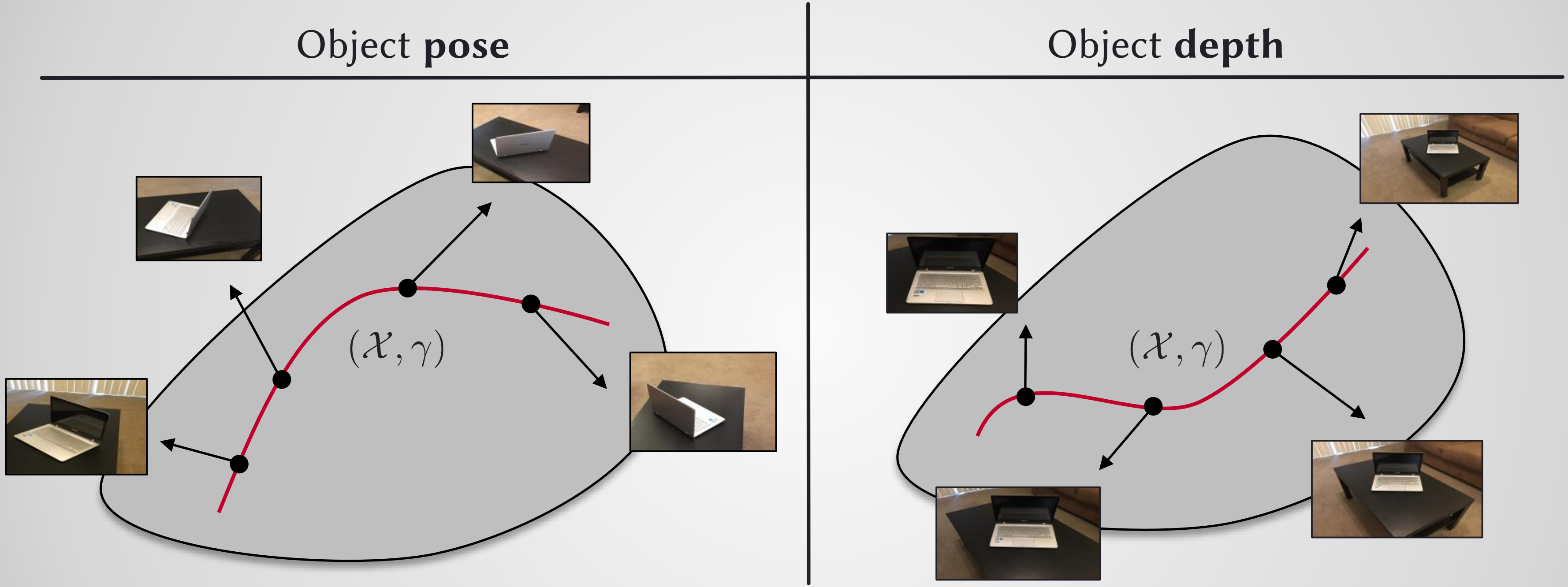
Learn trajectories in feature space

A Regression / Synthesis Problem



Transfer trajectories to unseen objects

Assumption



- Trajectories are parametrized by object pose and depth: Attributes
- Attributes assume a scalar value denoted by γ

Problem Formulation

$$\gamma : \mathcal{X} \to \mathbb{R}_+, \quad \mathbf{x} \mapsto \gamma(\mathbf{x})$$

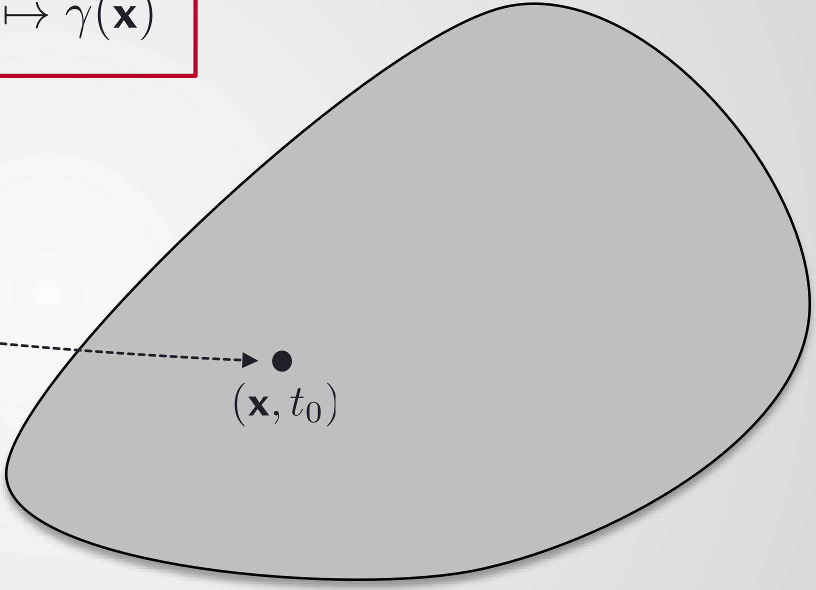
Object CNN

$\mathbf{x} \in \mathcal{X} \subseteq \mathbb{R}^d$

Attribute predictor

e.g., **depth** 2 [m]

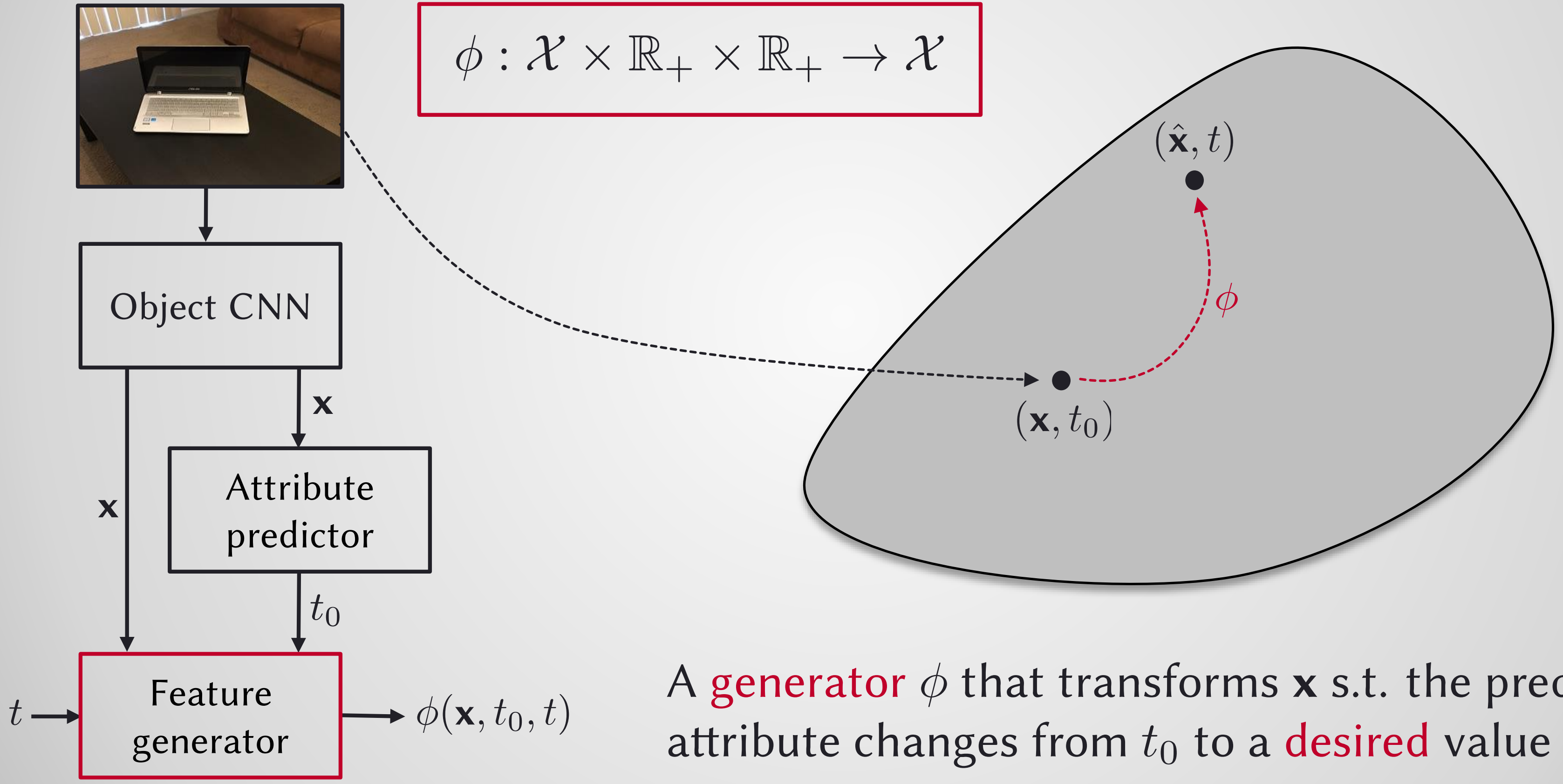
$\gamma(\mathbf{x}) = t_0 \in \mathbb{R}_+$



An attribute predictor γ trained on object CNN activations $\mathbf{x}$

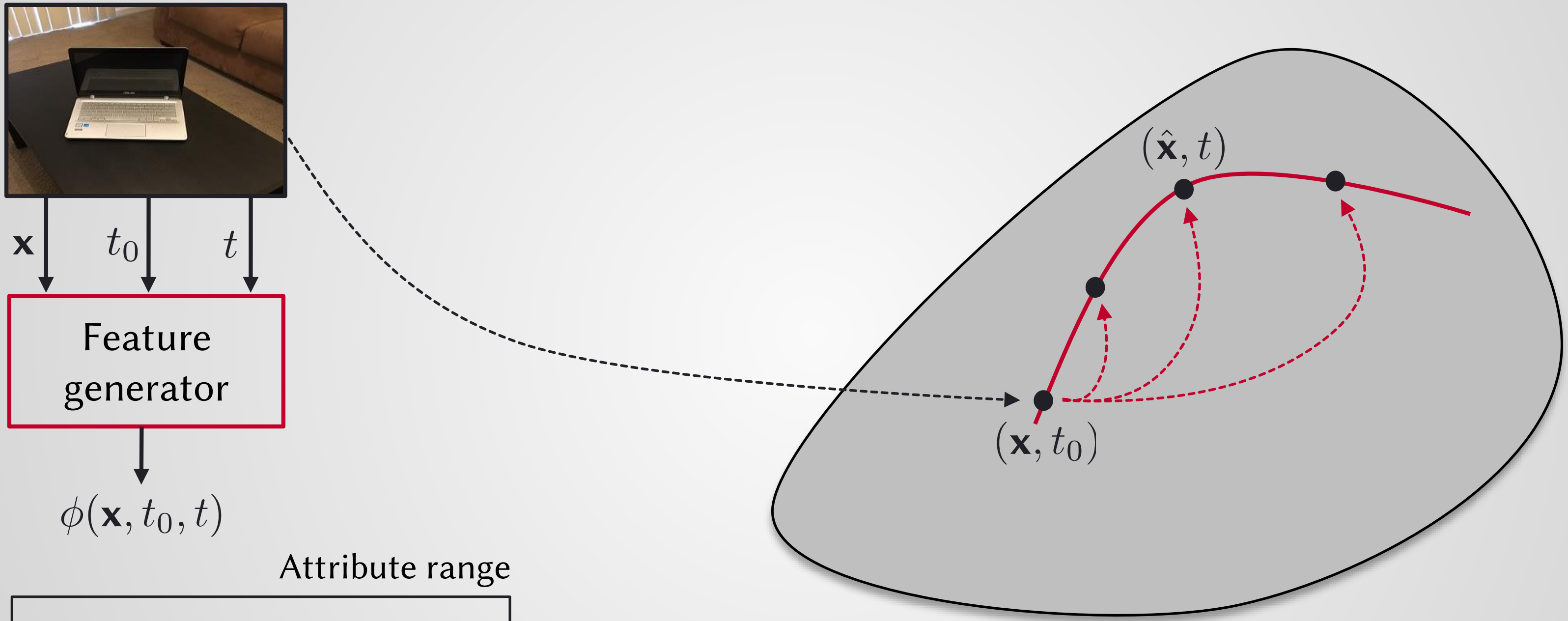
Problem Formulation

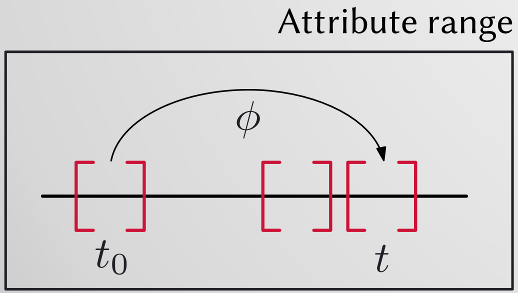
$$\boxed{\phi : \mathcal{X} \times \mathbb{R}_+ \times \mathbb{R}_+ \to \mathcal{X}}$$



A generator ϕ that transforms $\mathbf{x}$ s.t. the predicted attribute changes from t_0 to a desired value t

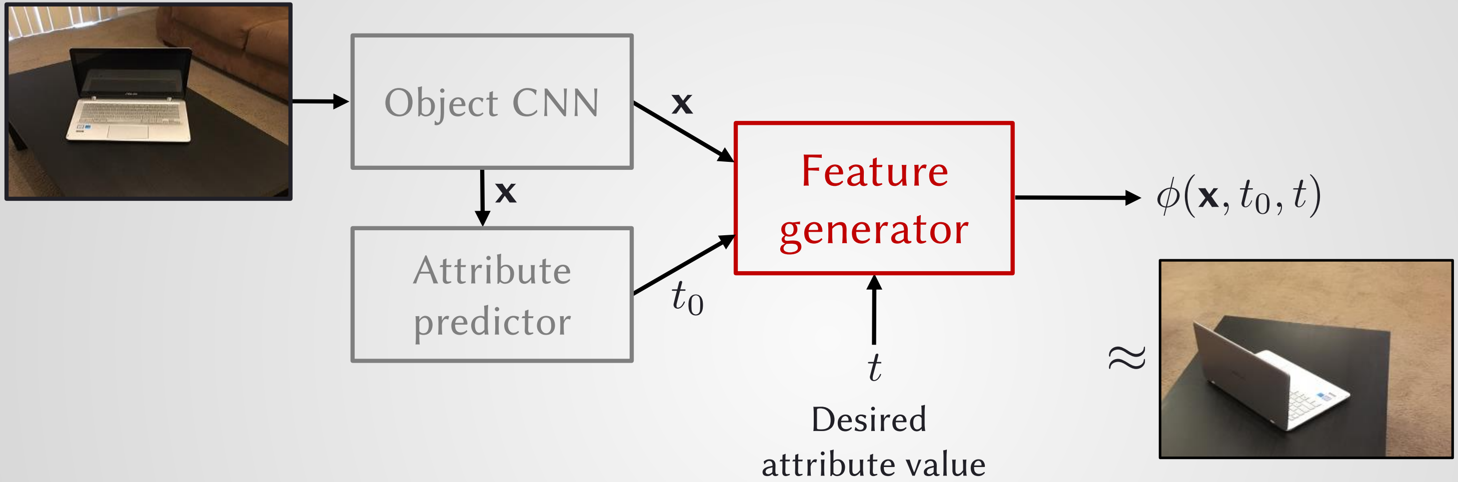
Problem Formulation





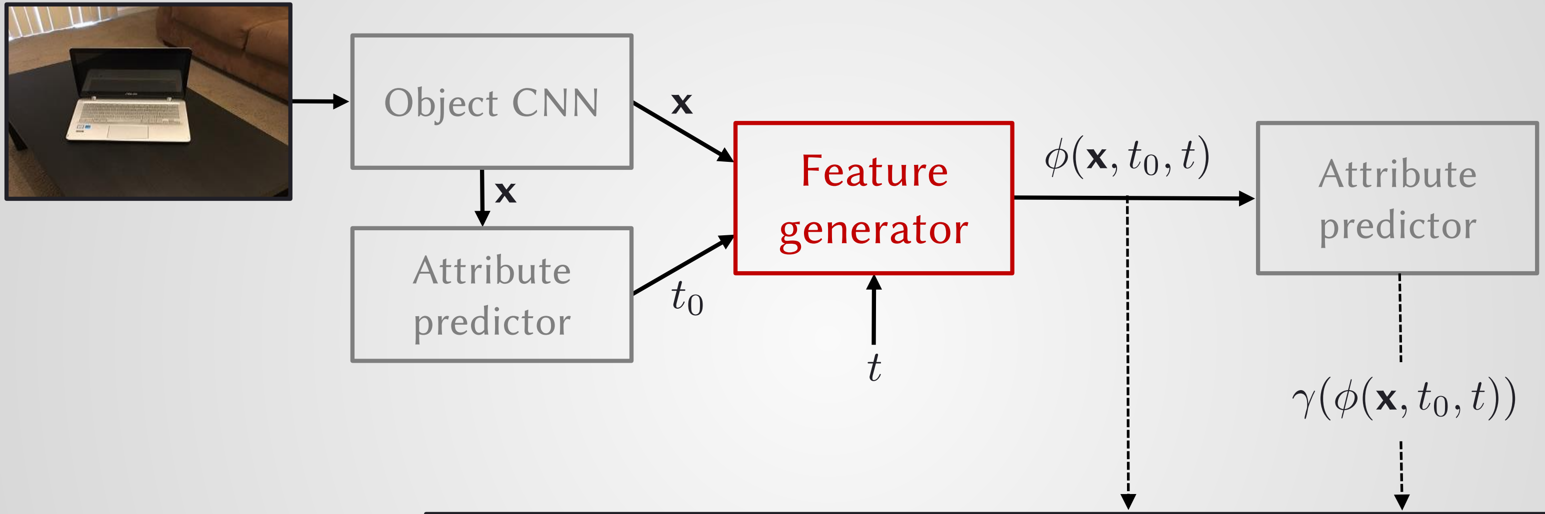
Generators trained for multiple pairs (t_0, t) can produce the attribute trajectory

Training for Synthesis



To **train** the generator for a given pair (t_0, t) we keep the object CNN and the attribute predictor frozen.

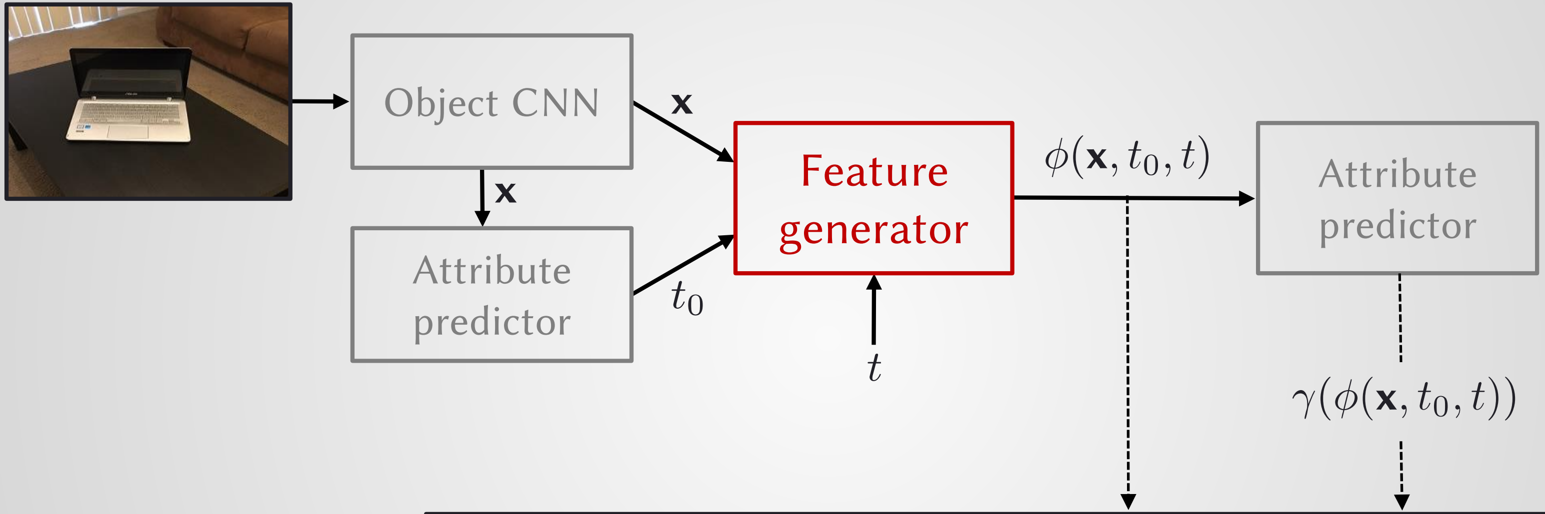
Training Loss for Synthesis



$$\mathcal{L}(\mathbf{x}, t; \phi) = \lambda \|\mathbf{x} - \phi(\mathbf{x}, t_0, t)\|^2 + [\gamma(\phi(\mathbf{x}, t_0, t)) - t]^2$$

The loss minimizes attribute mismatch between the synthesized sample and the desired attribute value.

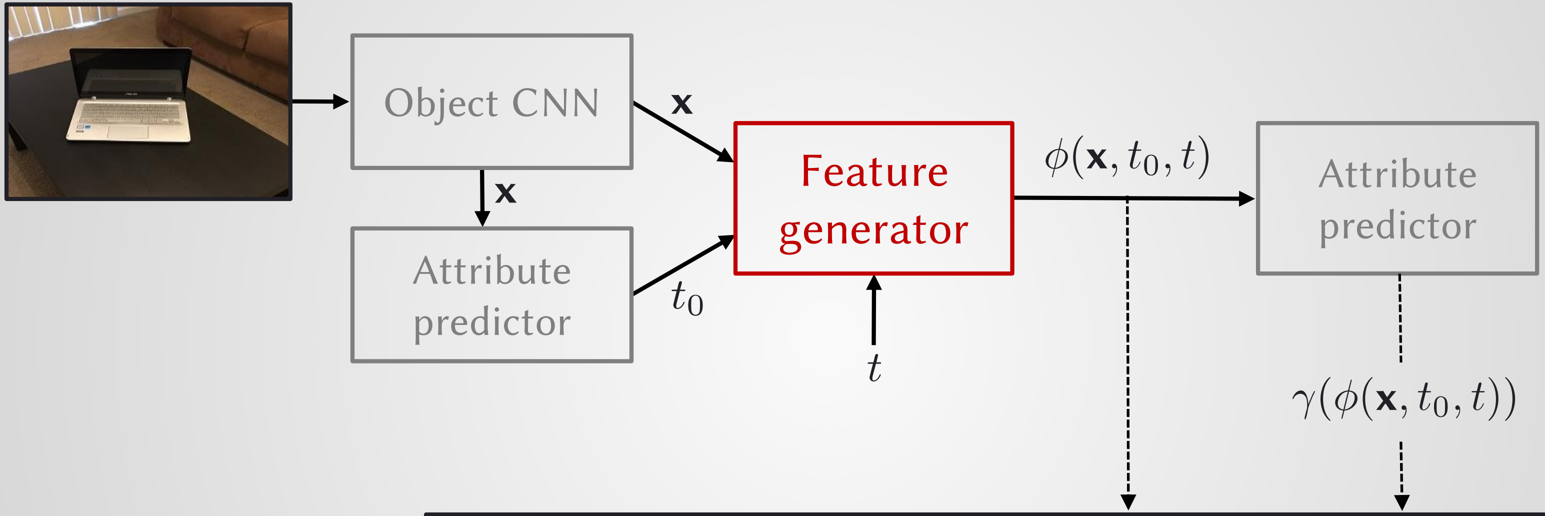
Training Loss for Synthesis



$$\mathcal{L}(\mathbf{x}, t; \phi) = \lambda \|\mathbf{x} - \phi(\mathbf{x}, t_0, t)\|^2 + [\gamma(\phi(\mathbf{x}, t_0, t)) - t]^2$$

... and **restrains** the synthesized sample to lie in the neighborhood of the original sample to preserve object identity.

Training Loss for Synthesis



$$\boxed{\mathcal{L}(\mathbf{x}, t; \phi) = \lambda \|\mathbf{x} - \phi(\mathbf{x}, t_0, t)\|^2 + [\gamma(\phi(\mathbf{x}, t_0, t)) - t]^2}$$

Note that learning only needs the given example $\mathbf{x}$ and a scalar value t

No paired data points

Training for Synthesis: Implementation

SUN RGBD dataset [Song et al. 2015]

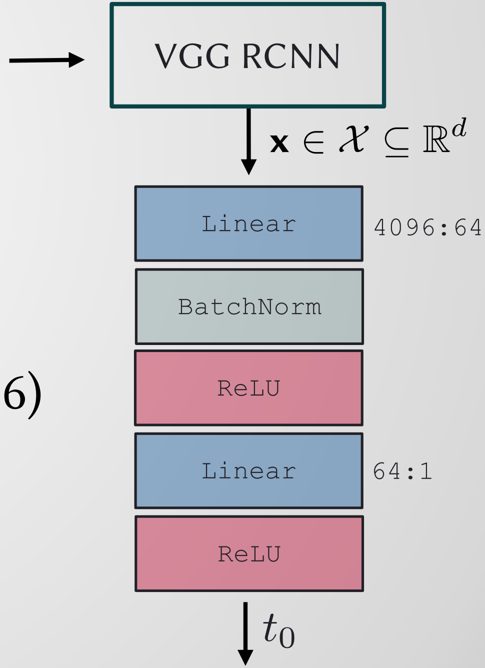
Images of 19 object classes along and their bounding boxes

Attributes: object pose and depth

- obtained from labeled 3D information

Training for Synthesis: Implementation

SUN RGBD dataset



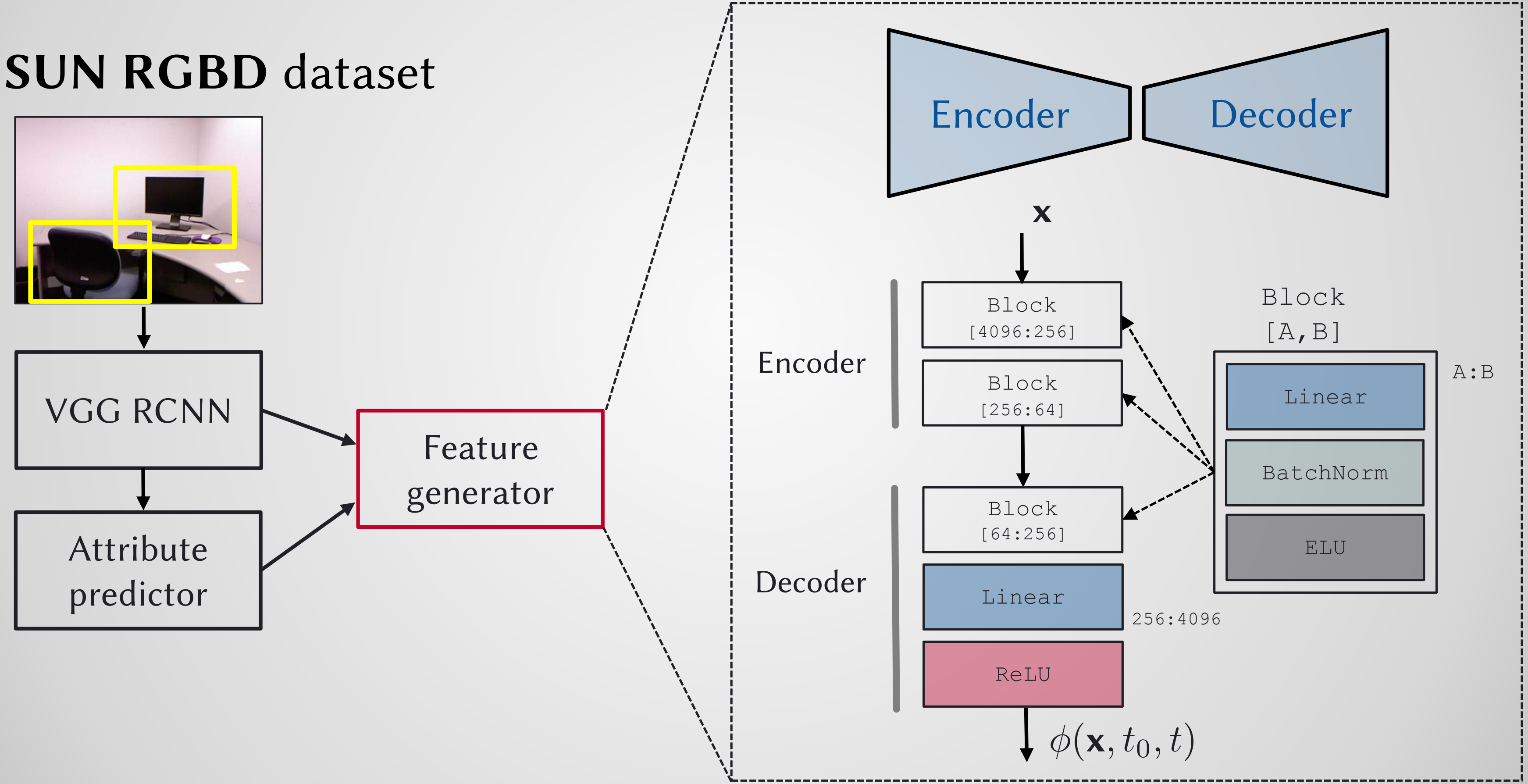
Training:

Fast-RCNN trained for object detection (VGG 16)

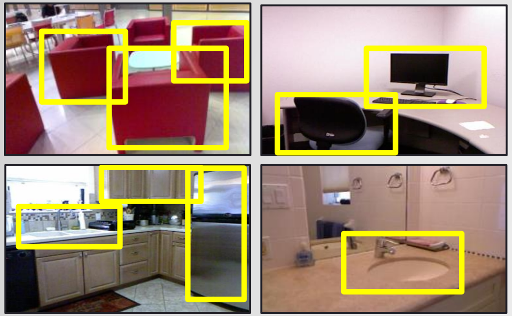
Attribute predictor trained for depth & pose

MLP on RCNN "FC" activations

Training for Synthesis: Implementation



Application: Transfer-Learning

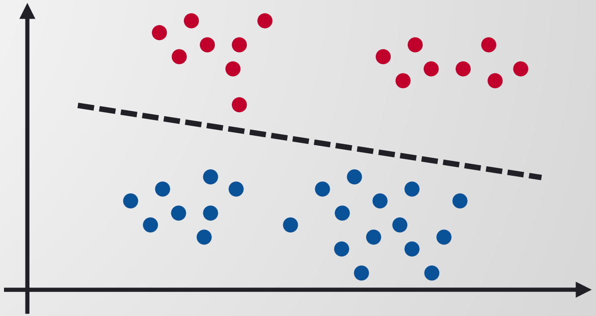


Source dataset

Object CNN

Transfer

Unseen target data



CNN activation space

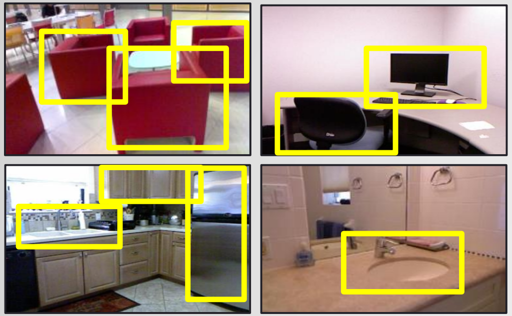
Source data : Object images with attribute labels

- 19 classes of SUN RGBD + depth & pose

Target data : Unseen object classes, no annotations

- 10 class subsets (T1, T2) from SUN RGBD

Application: One / Few-Shot Transfer

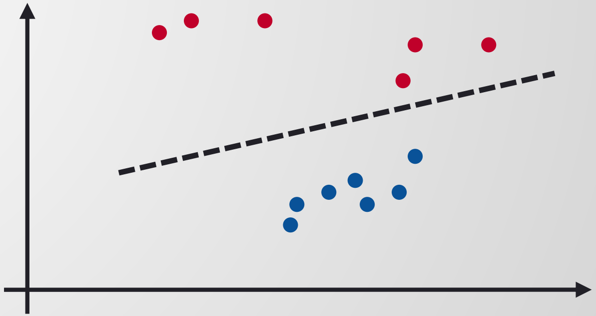


Source dataset

Object CNN

Transfer

Unseen target data



CNN activation space

Source data:

Training RCNN, Attribute predictor, Feature generator

Target data : Used for one-shot / few-shot object recognition

- Linear SVM trained with source RCNN activations

Application: One-Shot Object Recognition

For every image in **target dataset**, we

1. generate RCNN features: $\mathbf{x}$
2. predict it's depth / pose: t_0
3. synthesize features $\phi(\mathbf{x}, t_0, t)$ for a range of desired depths / poses t

Datasets	**Baseline***
T1	33.74
T2	23.76
T1 and T2	22.84

*Baseline ... Linear SVM trained on one-shot instances only

Application: One-Shot Object Recognition

For every image in **target dataset**, we

1. generate RCNN features: $\mathbf{x}$
2. predict it's depth / pose: t_0
3. synthesize features $\phi(\mathbf{x}, t_0, t)$ for a range of desired depths / poses t

Datasets	**Baseline***	**Pose Aug.**
T1	33.74	37.25
T2	23.76	27.15
T1 and T2	22.84	24.34

*Baseline ... Linear SVM trained on one-shot instances only

Application: One-Shot Object Recognition

For every image in **target dataset**, we

1. generate RCNN features: $\mathbf{x}$
2. predict it's depth / pose: t_0
3. synthesize features $\phi(\mathbf{x}, t_0, t)$ for a range of desired depths / poses t

Datasets	Baseline*	Pose Aug.	Depth Aug.
T1	33.74	37.25	38.32
T2	23.76	27.15	28.49
T1 and T2	22.84	24.34	25.52

*Baseline ... Linear SVM trained on one-shot instances only

Application: One-Shot Object Recognition

For every image in **target dataset**, we

1. generate RCNN features: $\mathbf{x}$
2. predict it's depth / pose: t_0
3. synthesize features $\phi(\mathbf{x}, t_0, t)$ for a range of desired depths / poses t

Datasets	Baseline*	Pose Aug.	Depth Aug.	D + P.	
T1	33.74	37.25	38.32	**39.10**	+5.36
T2	23.76	27.15	28.49	**30.12**	+6.36
T1 and T2	22.84	24.34	25.52	**26.67**	+3.83

*Baseline ... Linear SVM trained on one-shot instances only

Application: Few-Shot Object Recognition

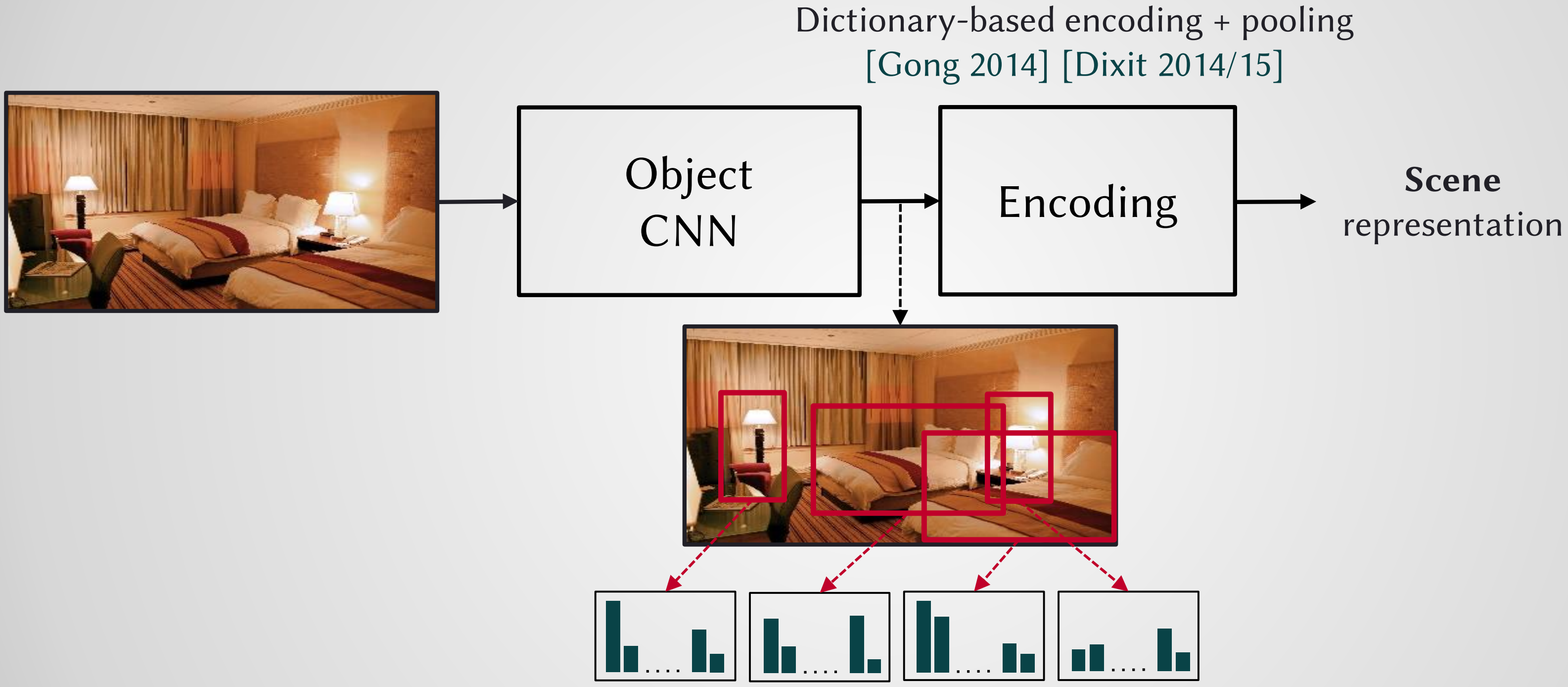
We repeat the previous experiment with 5 instances per target class

Datasets	Baseline*	Pose Aug.	Depth Aug.	D + P.	
T1	50.03	55.04	53.83	**56.92**	+6.89
T2	36.76	44.57	42.68	**47.04**	+10.28
T1 and T2	37.37	40.46	39.36	**42.87**	+5.50

In summary, we observe gains similar to one-shot (in the range of 5-10 points)

*Baseline ... Linear SVM trained on one-shot instances only

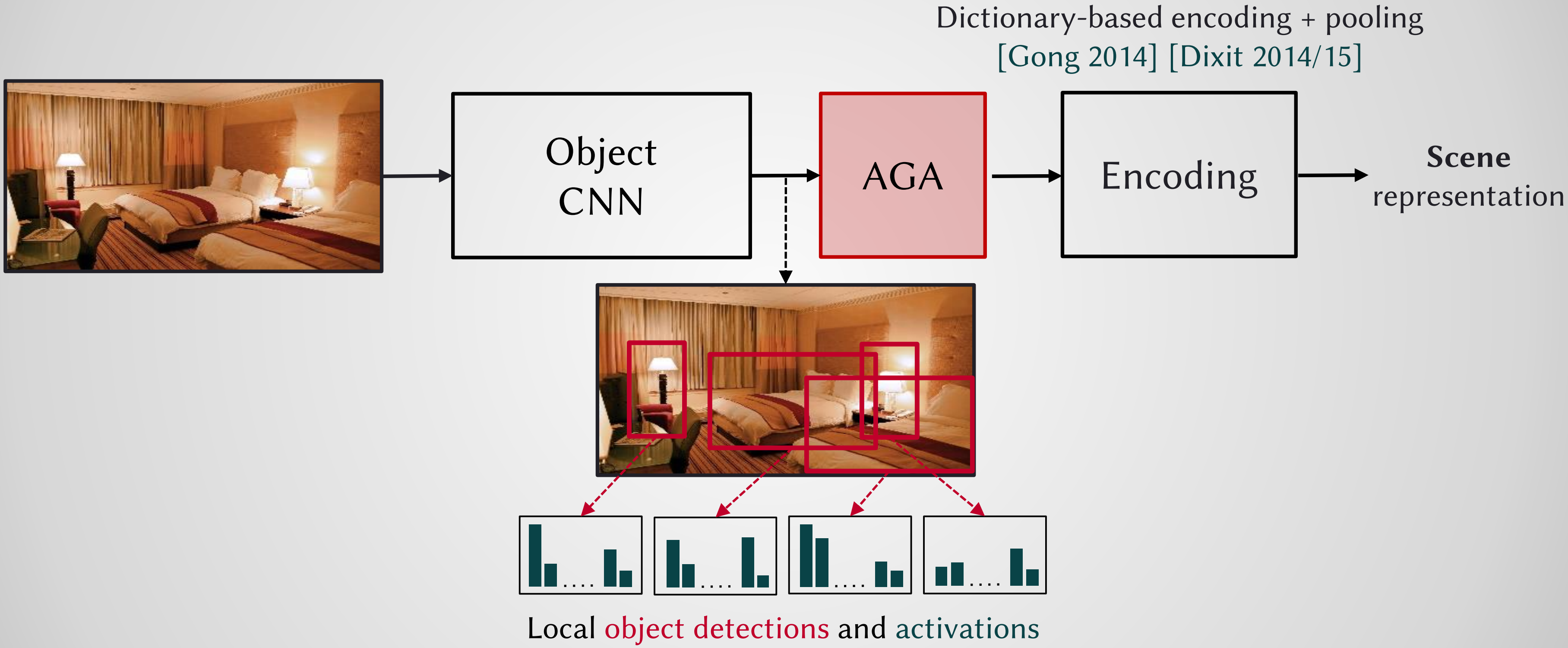
Object-based Scene Representation



Local object detections and activations

Problem: weak encoding due to few detections / image (more so in few-shot case)

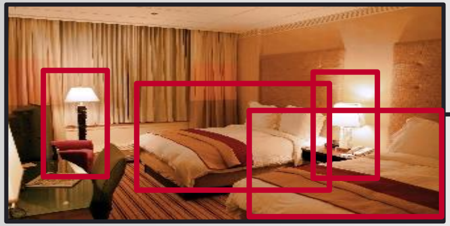
Object-based Scene Representation



Deploy pre-trained pose & depth guided synthesis to multiply the features

Application: One-shot Scene Recognition

Dictionary-based encoding + pooling
[Gong 2014] [Dixit 2014/15]



Object CNN → AGA → Encoding → **Scene** representation

Source Data: SUN RGBD

- Train feature synthesis

Target Data: Subset of MIT Indoor Scenes [Quattoni et al. 2012]

- Local feature extraction + depth / pose guided synthesis
- Scene Representation (Fisher vector) [Perronnin et al. 2010]
- Combined with state-of-the-art rep.: **Places** [Zhou et al. 2014], **Sem-FV** [Dixit et al. 2015]

Application: One-shot Scene Recognition

Approaches	Accuracy (%)
Sem-FV [Dixit et al. 2015]	32.75
AGA-augmented Sem-FV	**34.36**

Application: One-shot Scene Recognition

Approaches	Accuracy (%)
Sem-FV [Dixit et al. 2015]	32.75
AGA-augmented Sem-FV	**34.36**
Places CNN [Zhou et.al. 2014]	51.28
AGA-augmented Places CNN	**52.11**

Accuracy of **Sem-FV** and **Places CNN** representations improves non-trivially!

Conclusion

- We propose a technique for attribute-guided data augmentation (**AGA**)
- Augmentation in feature space of a CNN
  - Low complexity learning
  - Inherits the invariance of a pre-trained CNN
- Augmentation: Regression along attribute trajectories
  - Trajectories once learned can be transferred to unseen objects
- Attribute trajectory learning
  - Attribute predictor MLP
  - Feature regressor MLP
  - Training needs no paired examples
- Augmentation improves one shot/few-shot recognition

Thank You!

Source code (+ trained models for pose / depth) is publicly available!

This work is supported by **NSF** awards IIS-1208522, CCF-0830535 and ECCS-1148870.
We also thank **NVIDIA** for the generous donation of TitanX GPUs.

Supplementary Material

Implementation

- **Framework**: Torch
- **Optimizer**: ADAM [Kingma & Ba, 2015]

	Attribute strength predictor	Encoder-Decoder* (per attribute interval [a,b] to desired target t)
Learning rate	0.001	0.001
Batch size	300	300
Epochs	50	50
Loss	MSE	Weighted MSE (0.7 regularizer + 0.3 mismatch)

*pre-trained using all available data

Quality of Synthesized Examples

Objects (T1)	**Correlation coefficient**	**MAE** (Depth [m])	**Correlation coefficient**	**MAE** (Pose [degrees])
Picture	0.67	0.08	0.65	5.13
Ottoman	0.70	0.09	0.70	4.41
Whiteboard	0.67	0.12	0.65	4.43
Fridge	0.69	0.10	0.68	4.48
Counter	0.76	0.08	0.77	3.98
Book	0.74	0.08	0.73	4.26
Stove	0.71	0.10	0.71	4.50
Cabinet	0.74	0.09	0.72	3.99
Printer	0.73	0.08	0.72	4.59
Computer	0.81	0.06	0.80	3.73
Average	**0.72**	**0.09**	**0.71**	**4.35**

Quality of Synthesized Examples

Retrieval experiment

- Using synthesized samples we retrieve the nearest real sample from target database.
- Results expressed in
  - Top-1 retrieval accuracy (object class)
  - Coeff. of determination (attribute strength)
- Reasonable predictability of attr. strength for most objects classes.
- In others, at least class identity is retained

Objects (T1)	**Top-1**	**R^2**
Picture	0.33	0.36
Ottoman	0.60	0.12
Whiteboard	0.12	0.30
Fridge	0.26	0.08
Counter	0.64	0.18
Books	0.52	0.07
Stove	0.20	0.13
Cabinet	0.57	0.27
Printer	0.31	0.02
Computer	0.94	0.26
Average	**0.72**	**0.09**