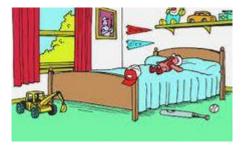
# Cross-Modal Scene Representations

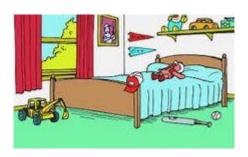
Lluís Castrejón University of Toronto

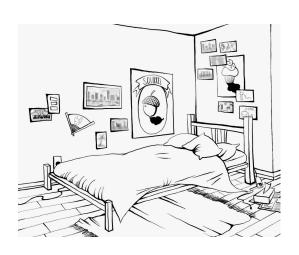








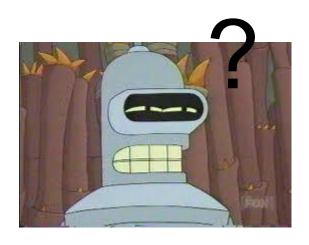


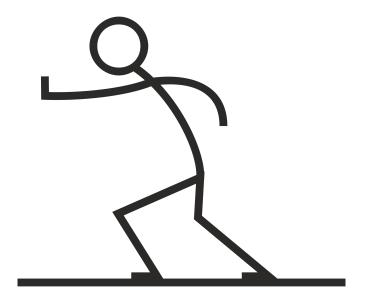




A fire-ship attack on our port. Frigates burned in their berths, honest merchant-men losing their livelihoods. The sacking of the township. Women cut down in their homes. Innocents slaughtered. This must not go unanswered. So I stand in solitude. And I pray. I pray that I am forgiven. I pray that we Dutch are given the year to rebuild our lost vessels and recruit fresh men. That we will right the wrongs done by Charles of England. That renewed, we will take this fight back to England. But this destruction, this murder cannot remain unaddressed. I pray that the sparks of the same fire that burned Schelling are blown across the water to England. That God brings down His fire upon the English and that we Dutch are avenged. That we are spared the necessity of retaliation in the new martial season. I pray that this is done soon, so that God's will is seen. Amen.





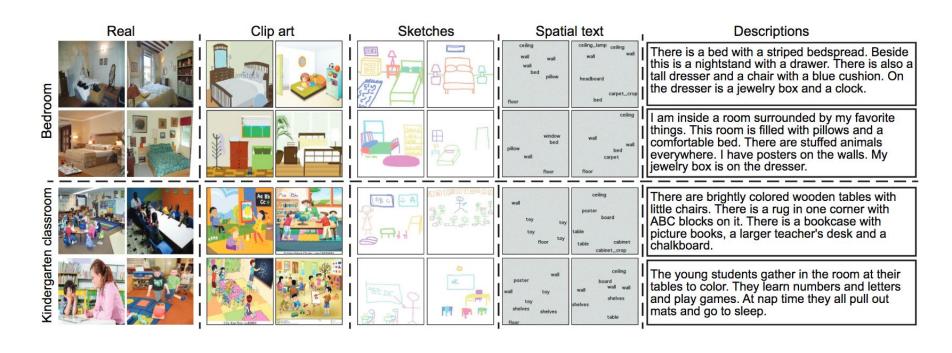








## **Cross-Modal Scene Understanding**



## **CMPlaces**

## Dataset of 205 scene categories

#### Line drawings:

6,644 training + 2,050 validation examples



#### **Clipart:**

11,372 training + 1,954 validation examples



#### **CMPlaces**

## Dataset of 205 scene categories

#### **Text Descriptions:**

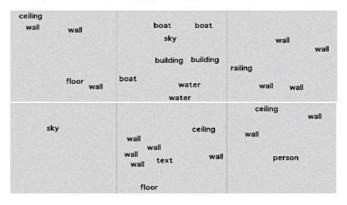
4,307 training + 2,050 validation examples

There are brightly colored wooden tables with little chairs. There is a rug in one corner with ABC blocks on it. There is a bookcase with picture books, a larger teacher's desk and a chalkboard.

I am inside a room surrounded by my favorite things. This room is filled with pillows and a comfortable bed. There are stuffed animals everywhere. I have posters on the walls. My jewelry box is on the dresser.

#### **Spatial Text:**

456,300 training + 2,050 validation examples



#### **CMPlaces**

## Dataset of 205 scene categories

Natural images (Places dataset): 2M training + 20,500 validation examples



Scene categories include Art Gallery, Bedroom, Office, Restaurant, River, Airfield, Bar, Canyon ...

## Strong vs weak alignment

#### **Strong Alignment (Pairs)**



a man holding a white snow board by some other kids

- Cross modal embedding with pairs
- CCA, Joint space embedings, etc.

#### Weak Alignment (Category Level)



There are brightly colored wooden tables with little chairs. There is a rug in one corner with ABC blocks on it. There is a bookcase with picture books, a larger teacher's desk and a chalkboard.

- Samples are aligned in category level only
- No object level alignment, i.e. no pairs

## Strong vs weak alignment

#### Not scalable!

#### **Strong Alignment (Pairs)**



a man holding a white snow board by some other kids

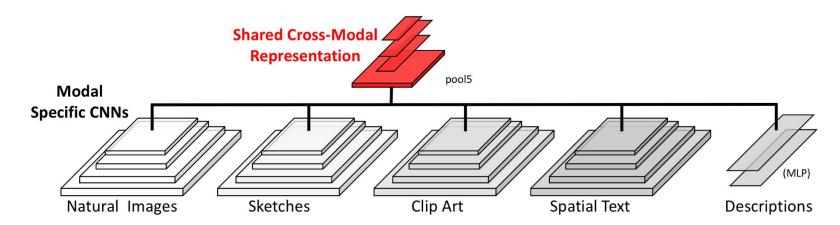
- Cross modal embedding with pairs
- CCA, Joint space embedings, etc.

#### **Weak Alignment (Category Level)**



There are brightly colored wooden tables with little chairs. There is a rug in one corner with ABC blocks on it. There is a bookcase with picture books, a larger teacher's desk and a chalkboard.

- Samples are aligned in category level only
- No object level alignment, i.e. no pairs

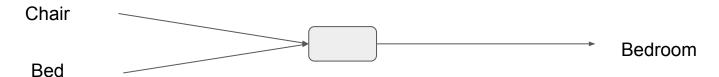


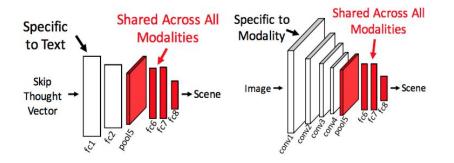
- Inputs from five modalities with different low-level statistics
- Represent all modalities in a high-level shared space

**Problem:** Parts of the network specialize to certain domains

**Solution:** Use regularization to enforce alignments

#### A) Modality Tuning

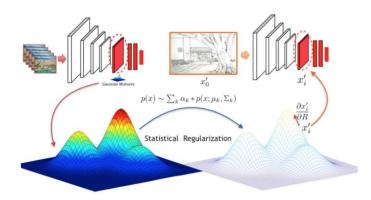




**Step 1:** Train network with higher-level layers initialized and fixed from Places CNN.

**Step 2:** Higher-level layers are released and the model is further fine-tuned end-to-end.

#### **B) Statistical Regularization**



$$\min_{w} \underbrace{\sum_{n} \mathcal{L}(z(x_{n}; w), y_{n})}_{\text{Softmax Loss}} + \underbrace{\sum_{n, i} \lambda_{i} \cdot \mathcal{R}_{i} \left(h_{i}(x_{n}; w)\right)}_{\text{Statistical}}$$
Statistical Regularization

Regularize activations in the shared layers to follow similar statistics across modalities.

Shared statistics estimated from a large dataset (Places) and modeled by a parametric distribution. We experimented with:

- Gaussian
- Gaussian Mixture Model

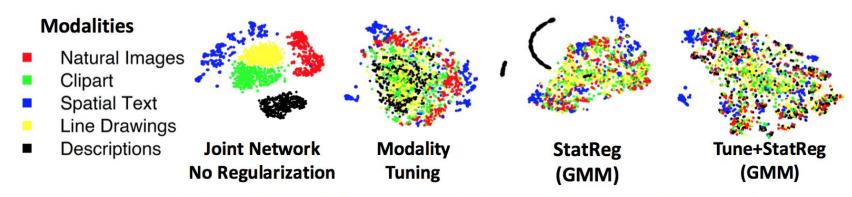
#### **Regularization Term:**

$$\mathcal{R}_i(h) = -\log P_i(h; \theta_i)$$

#### StatReg with GMM:

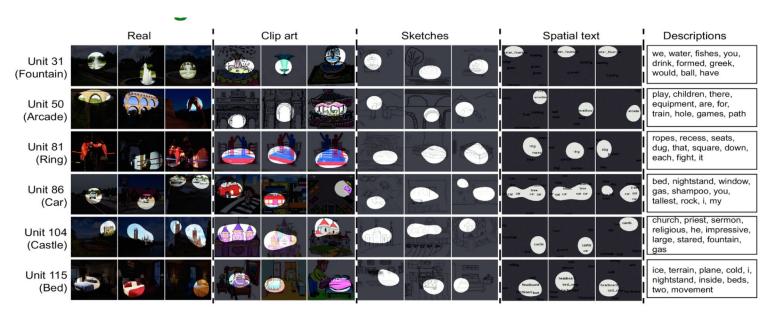
$$\mathcal{R}_{i}(h; \alpha, \mu, \Sigma) = -\log \sum_{k=1}^{K} \alpha_{k} \cdot P_{k}(h; \mu_{k}, \Sigma_{k})$$

## T-SNE



Random samples from all five modalities are embedded onto a 2D space via t-SNE on fc7 features

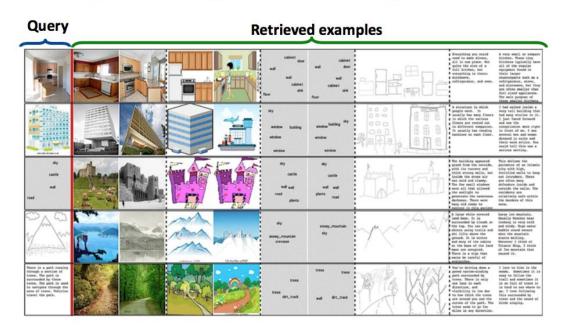
## Visualizing Activations



Units emerge in our *pool5* representation that fire on concepts independently of the modality

## **Cross-Modal Retrieval**

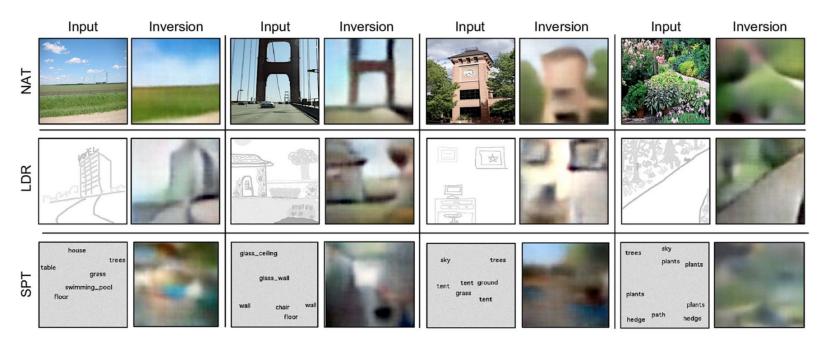
Given a query in one modality, we retrieve nearest neighbors in other modalities



## **Cross-Modal Retrieval**

Cross Modal Retrieval	Query	NAT				CLP				SPT				LDR				DSC				Mean
	Target	CLP	SPT	LDR	DSC	NAT	SPT	LDR	DSC	NAT	CLP	LDR	DSC	NAT	CLP	SPT	DSC	NAT	CLP	SPT	LDR	mAP
BL-Ind		17.8	15.5	10.1	0.8	11.4	13.1	9.0	0.8	9.0	10.1	5.6	0.8	4.9	7.6	6.8	0.8	0.6	0.9	0.9	0.9	6.4
BL-ShFinal		10.3	13.5	4.0	12.7	7.2	8.7	2.8	8.2	8.1	5.7	2.2	9.3	2.4	2.5	3.1	3.2	3.3	3.4	8.5	2.4	6.1
BL-ShAll		15.9	14.2	9.1	0.8	8.9	10.9	7.0	0.8	8.4	7.4	4.2	0.8	4.3	5.6	5.7	0.8	0.6	0.9	0.9	0.9	5.4
A: Tune		12.9	23.5	5.8	19.6	9.7	15.5	4.0	13.7	19.0	13.5	5.6	24.0	4.1	3.8	5.8	5.9	6.4	4.5	9.5	2.5	10.5
A: Tune (Free)		14.0	29.8	6.2	18.4	9.2	17.6	3.7	12.9	21.8	15.9	6.2	27.7	3.7	3.1	6.6	5.4	5.2	3.5	10.5	2.1	11.2
B: StatReg (Gaussian)		18.6	20.2	10.2	0.8	11.1	15.4	8.5	0.8	13.3	15.1	7.7	0.8	4.7	6.6	6.9	0.9	0.6	0.9	0.8	0.9	7.2
B: StatReg (GMM)		17.8	23.7	9.5	5.6	13.4	18.1	8.9	4.6	16.7	16.2	8.8	5.3	6.2	8.1	9.4	3.3	3.0	4.1	4.6	2.8	9.5
C: Tune + StatReg (GMM)		14.3	32.1	5.4	22.1	10.0	19.1	3.8	14.4	24.4	17.5	5.8	32.7	3.3	3.4	6.0	4.9	15.1	12.5	32.6	4.6	14.2

## Inverting the representation



We used up-convolutional networks for inversion [Dosovitskiy & Brox]

# Thanks!

http://cmplaces.csail.mit.edu/







