Università
degli Studi
di Padova

Crowd Counting

Convolutional Neural Networks of Density Maps

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What is crowd counting?

It's the task of estimating the number of people in an image.

Crowd counting is challenging due to:

- Scale variations
- Limited size of available datasets
- Non-uniform distribution of people
- Object occlusions
- Illumination issues
- Blurred frames

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Motivation

Crowd counting is useful for:

- Overcrowding detection
- Crowd scene analysis
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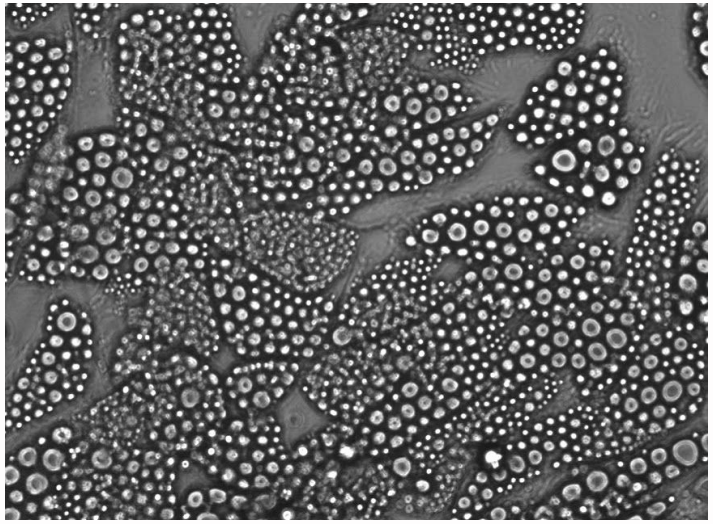
It can also be generalized to other problems:

- Vehicle counting
- Biological cell counting



Traditional approaches

Detection-based methods

- Use visual object detectors
- Sum up the occurrences of detected objects
- Limited by occlusions and background cluttering

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- They try to learn a relation from image features to people count
- A linear mapping is improbable and difficult to learn (Pham et al.)
- Random forest regression methods can learn a non-linear mapping between local features and density maps

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- Random forest regression methods can learn a non-linear mapping between local features and density maps

More on density maps later

CNN-based approaches

Many methods have been tried

- CNN that maps each image frame to its crowd-count value (Wang et al.)
- Train on crowd density and crowd count alternatively (Zhang et al.)
- These approaches didn't generalize well with scale variations
- They usually require too many epochs and parameters

More recently:

- Cao et al. proposed SANet, an encoder-decoder network for accurate crowd counting
- Li et al. proposed combining VGG-16 with dilated convolutional layers in CSRNet
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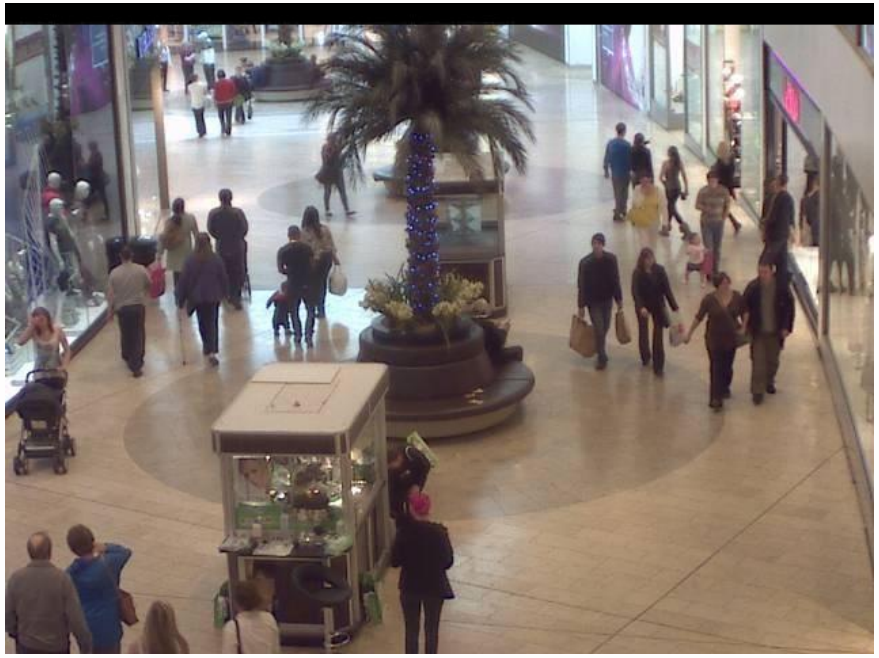
No clear winner...

Datasets

Dataset: Mall

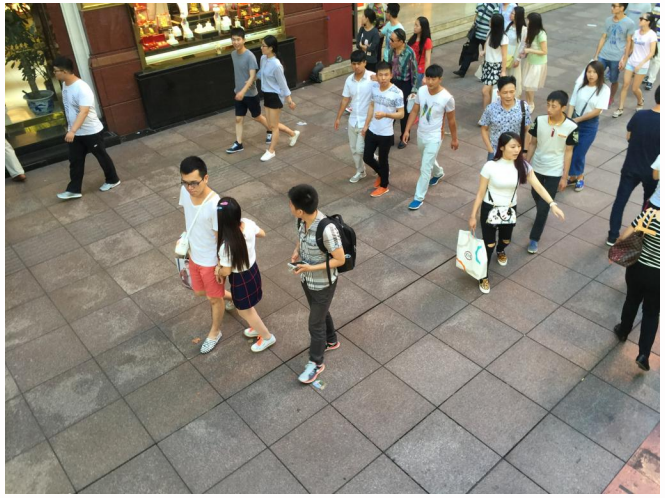
- 2000 RGB frames
- Fixed frame size: 640x480 pixels
- (😔) Same scene recorded from a security camera in a Mall
- (😔) The top of every image has a black band



Dataset: Shanghai Tech

- Actually 2 datasets: Part A and Part B
  - Part A has 700 images
  - Part B has 498 images
- 1198 RGB frames in total

- ~330.000 head coordinates
- Different frame sizes
- (😋) Different viewpoints
- (😋) Various conditions



Preprocessing

Mall dataset:

- Remove the black top 16 pixels from images
- Random data split (80/20)

Shanghai Tech datasets:

- Extract ground truth head-point coordinates from `*.mat` files to `numpy` files

Both datasets:

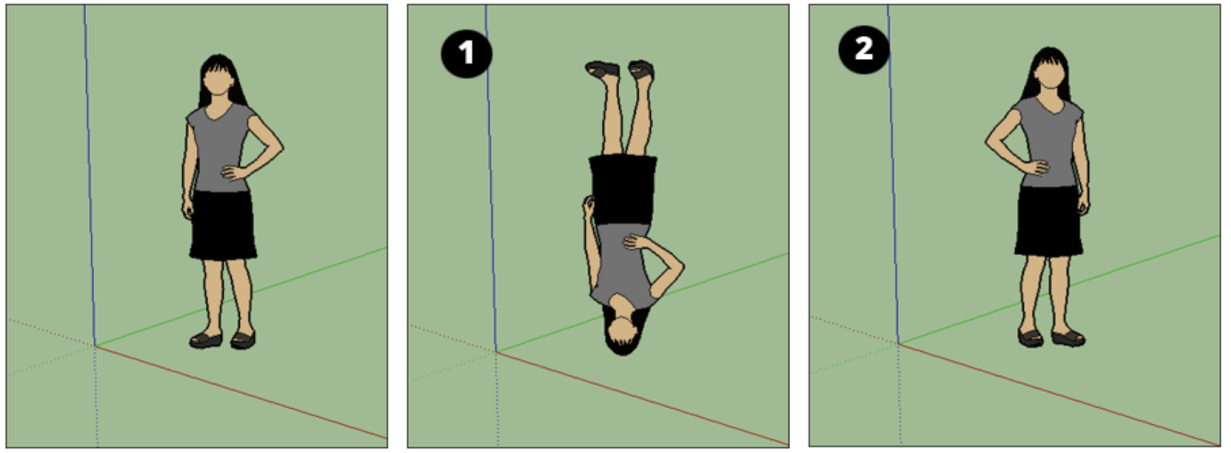
- Extract ground truth count from `*.mat` files to `CSV` files

Data augmentation

- The datasets are very small
- Hard to find datasets with head points, they require a lot of manual effort
- Provide scale, rotation and flips invariance
- (equivariance for density maps as we will see)

We then applied to each image batch:

- Random flips (horizontal)
- Random rotations
- Random resizing and rescaling



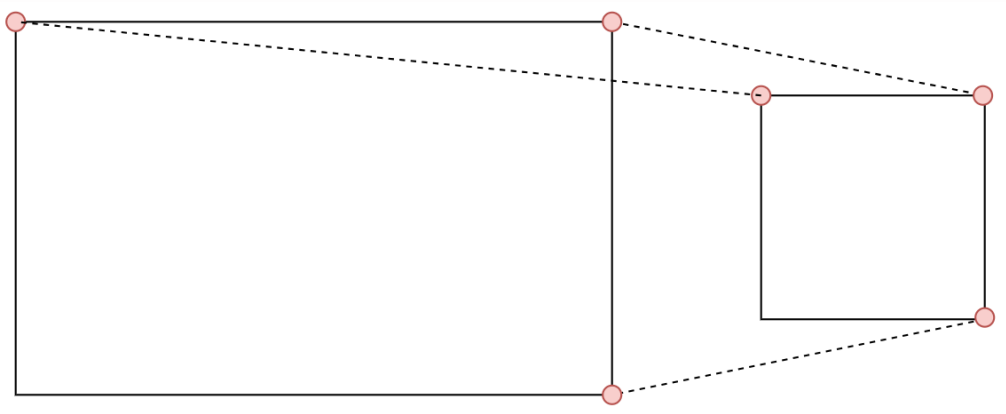
How do we adapt the ground truth to the resized images?

Affine transformations (1)

Given sets of coordinates (x_i, y_i) in the original image and (x'_i, y'_i) in the resized image:

- Infer the transformation matrix that maps (x_i, y_i) to (x'_i, y'_i) using 3 extreme points
- Use `map_matrix` to transform the ground truth points to the new scale

$$\begin{bmatrix} x'_i \\ y'_i \end{bmatrix} = \texttt{map\_matrix} \cdot \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}$$

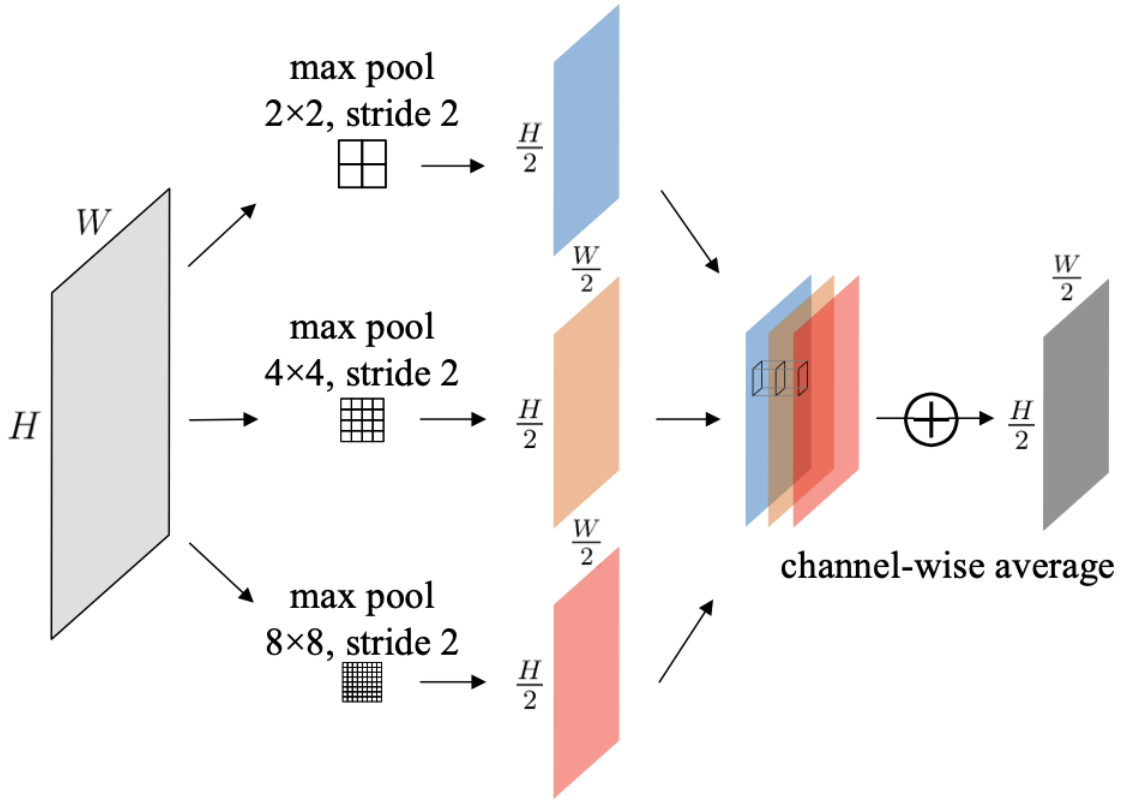


Affine transformations (2)

A first attempt

- CNN with Multi-Kernel pooling
- Output layer: single neuron
- Predicts automatically the crowd count

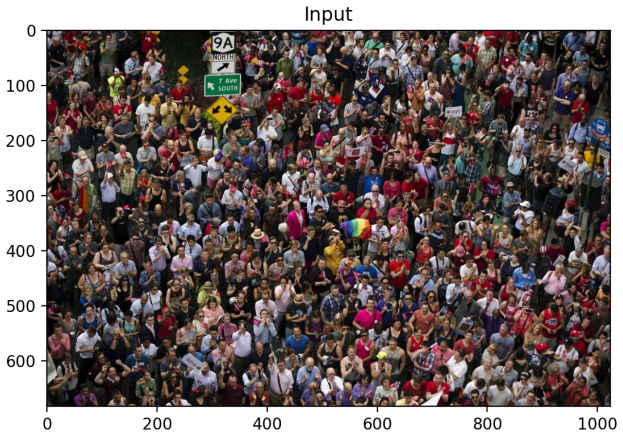
However: **overfitting**

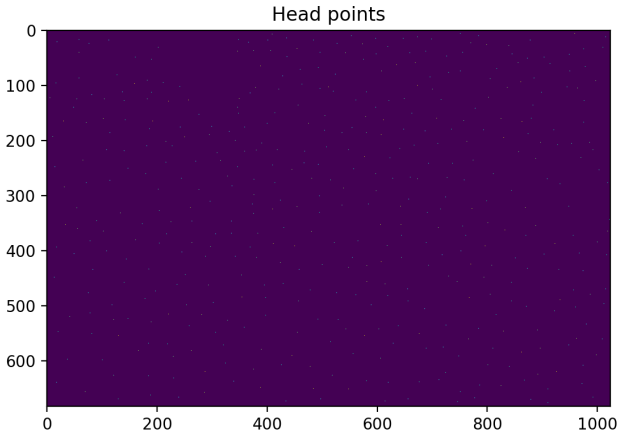


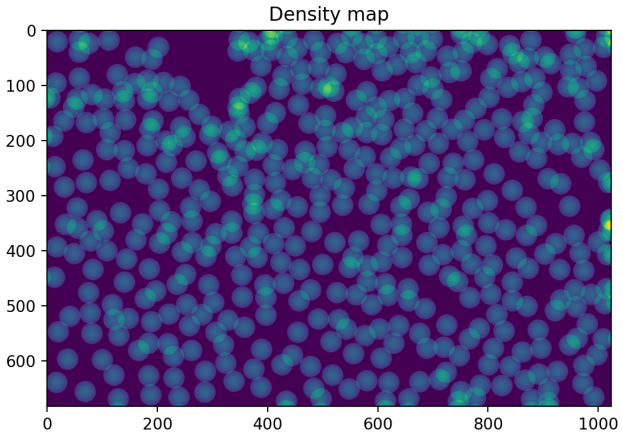
Methods & Experiments

Density maps

- Exploit all ground-truth information
- Convert head points into a map
- Create an image with head points
- Convolution with a Gaussian Kernel







Density maps

Gaussian kernel:

- Size: 91x91 pixels
- $\sigma = 15$
- All values below 0.0003 are set to 0
- Normalization: sum to 1

1/273

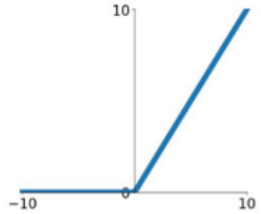
1	4	7	4	1
4	16	26	16	4
7	26	41	26	7
4	16	26	16	4
1	4	7	4	1

Architecture

- Transfer learning: VGG16 pre-trained on ImageNet
- Removed fully connected layers
- Upsampling through transposed convolutional layers
- Convolution Kernel size: 3×3, stride 1×1
- Activation: ReLU

ReLU

$\max(0, x)$



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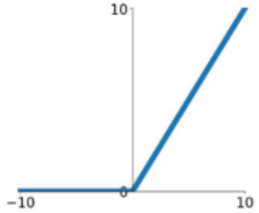
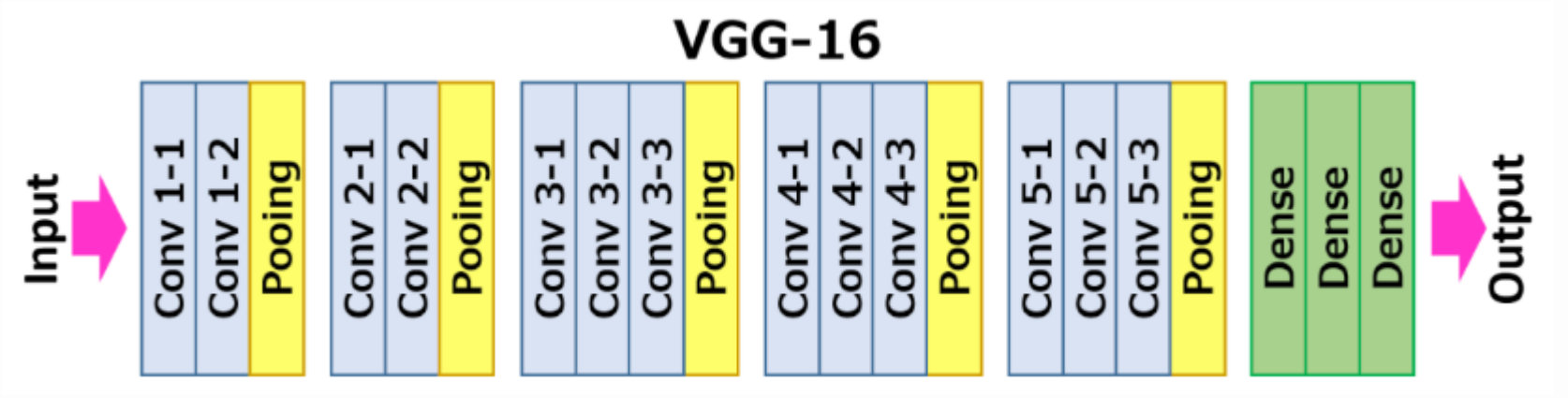
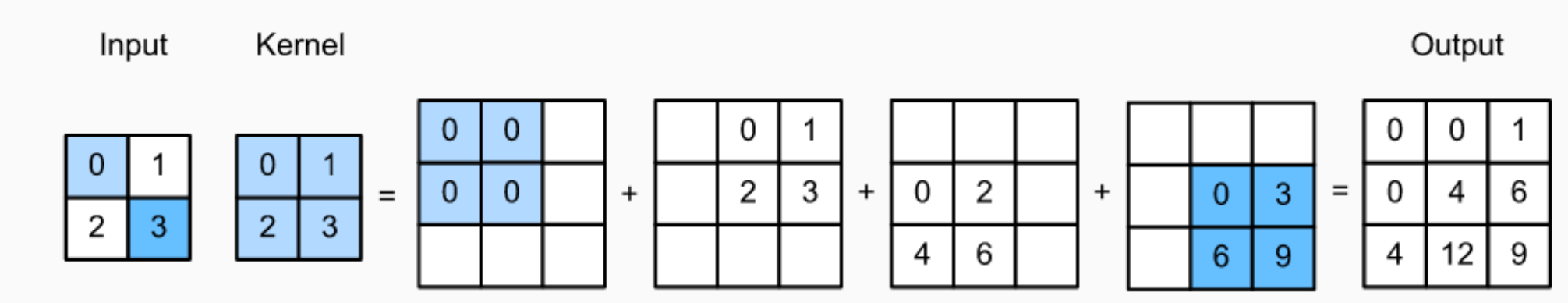




Transpose convolution

- Upsampled convolution
- Kernel size: 2×2, stride 2×2
- Activation: ReLU



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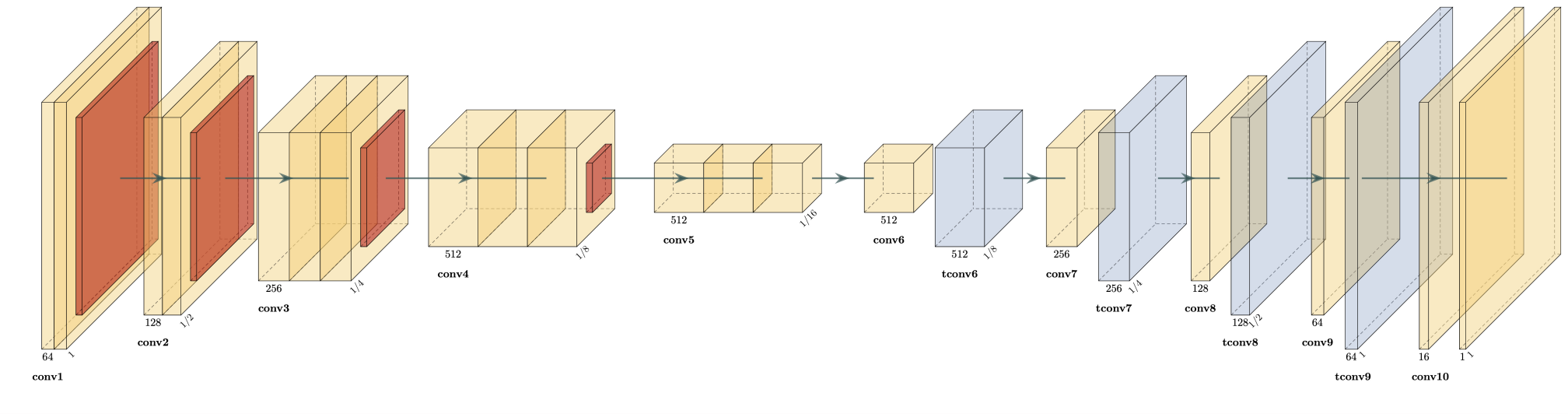
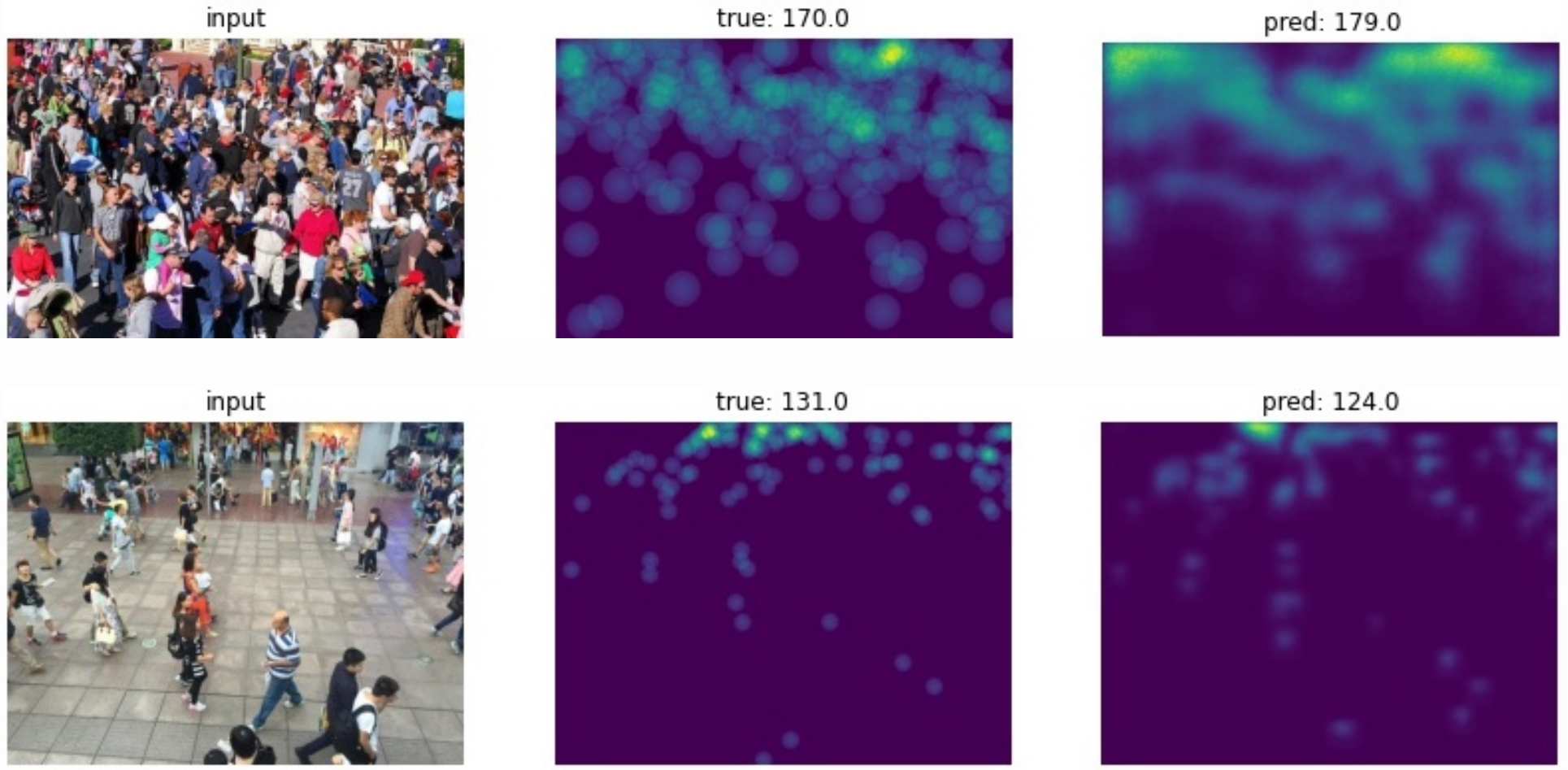


Training

- Batch size: 1
- Online data augmentation
- Learning rate: from $1e-5$ to $1e-7$
- Optimizer: Adam
- Alternating between Shanghai Tech A and B every 2 epochs
- Loss: euclidean distance $L_c = (y - \hat{y})^2$
- Best validation loss after 126 epochs

Prediction

Examples:



Metrics

$\hat{z}_i$: prediction
z_i: ground truth

- $\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |\hat{z}_i - z_i|$
- $\mathrm{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (\hat{z}_i - z_i)^2}$
- $\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N} \frac{|\hat{z}_i - z_i|}{z_i} * 100$

Results

	Part A			Part B		
Method	**MAE**	**MSE**	**MAPE**	**MAE**	**MSE**	**MAPE**
Zhang et al. (Cross-scene CNN, 2015)	181.8	277.7		32.0	49.8	
Zhang et al. (Multi-column CNN, 2016)	110.2	173.2		26.4	41.3	
Babu Sam et al. (Switching CNN, 2017)	90.4	135.0		21.6	33.4	
Sindagi et al. (CP-CNN, 2017)	73.6	106.4		20.1	30.1	
Liu et al. (2018)	72.0	106.6		14.4	23.8	
Liu et al. (2018)	73.6	112.0		13.7	21.4	
Ours	92.8	148.2	28.2%	16.9	28.1	22.8%

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Resources:

- Google Cloud VM
- 8CPUs, 52 GB RAM
- 1 NVIDIA Tesla T4

Conclusions

Our contribution

- A novel CNN for high-resolution density maps prediction
- A novel approach for data augmentation
- A full explanation on how to predict density maps

What we learned

- Hands-on experience with a CV task
- Preprocessing
- Transfer learning
- Importance of data
- How to design a model
- Google Cloud Platform
- Experience with state-of-the-art research paper

Future work

- More accurate loss function
- Adaptive gaussian kernel
- Different baseline networks (SqueezeNet, Xception)
- Dilated convolution
- Main problem: small dataset

Thank you for your attention

Questions?