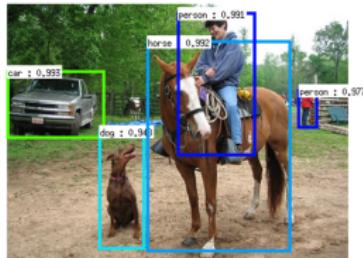


# OBJECT DETECTION USING THE SCATTERING TRANSFORM

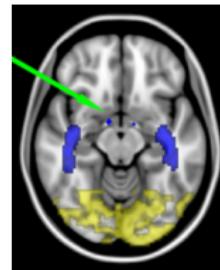
Marius Hobbahn

February 18, 2019

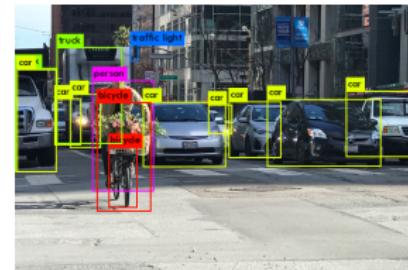
# OBJECT DETECTION



(A)



(B)



(C)

- ▶ Automatic annotation of everyday photos
- ▶ Brain disease recognition
- ▶ Traffic scene detection

# MOTIVATION

## PROBLEMS

1. Loads of data necessary for training
2. Capability to generalize unclear for different circumstances  
(i.e. invariances w.r.t. many things)

## POSSIBLE SOLUTIONS

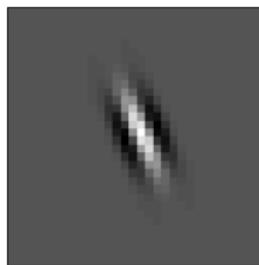
1. Filters that generalize quickly
2. Theoretical bounds for some invariances (i.e. translation, location)

# SCATTERING TRANSFORM

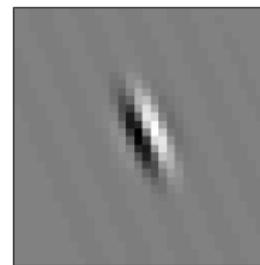
## BASIC IDEA

Static image filter that has certain theoretical guarantees with respect to invariances (i.e. location, scale, rotation).

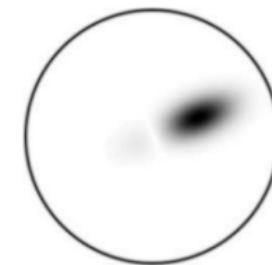
$$\psi(u) = C_1(e^{iu \cdot \xi} - C_2)e^{\frac{-|u|^2}{2\sigma^2}} \quad (1)$$



(a)



(b)



(c)

FIGURE 1: Complex morlet wavelet. a) Real part of  $\psi$ . b) Imaginary part of  $\psi$ . c) Fourier modulus  $|\hat{\psi}|$ .

# VISUALIZATION OF THE FILTER BANK

Wavelets for each scales  $j$  and angles  $\theta$  used, with the corresponding low-pass filter.  
The contrast corresponds to the amplitude and the color to the phase.

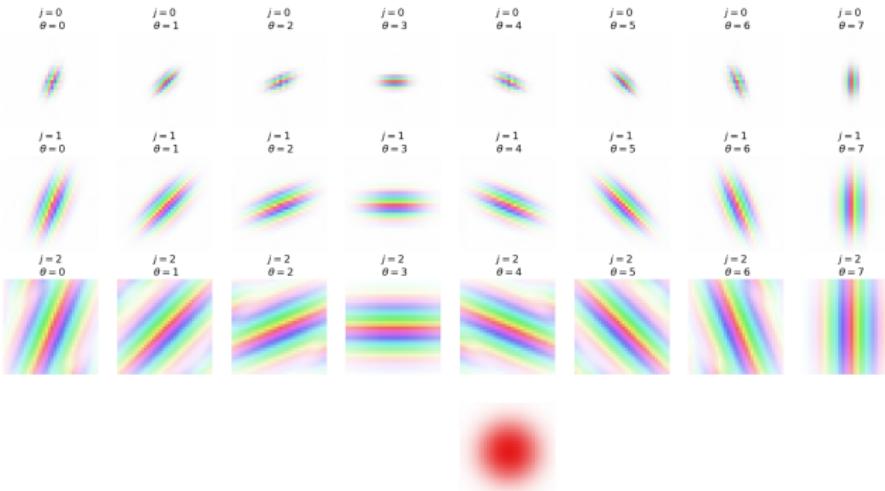


FIGURE 2: Visualization of the filter bank

# SCATTERING NETWORKS

## BASIC IDEA

Apply the scattering transform multiple times to get higher order scattering coefficients.

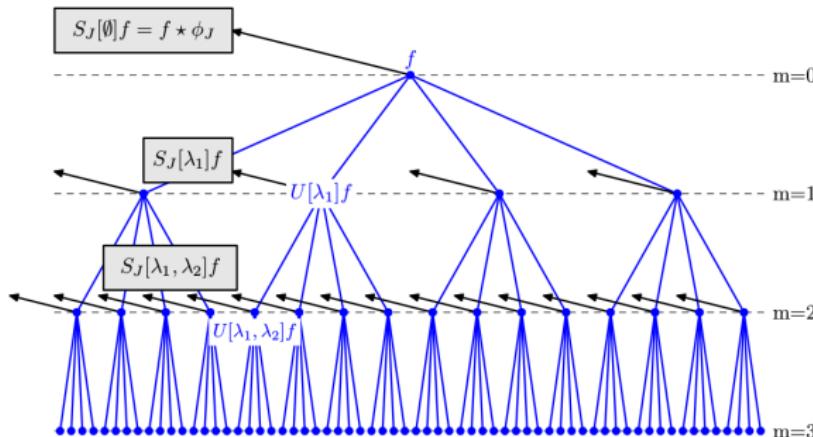


FIGURE 3

# VISUALIZATION OF THE SCATTERING COEFFICIENTS

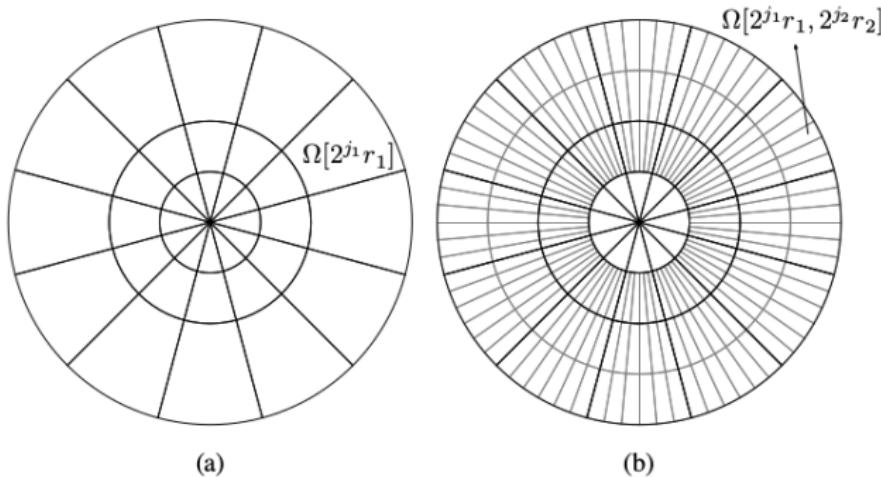
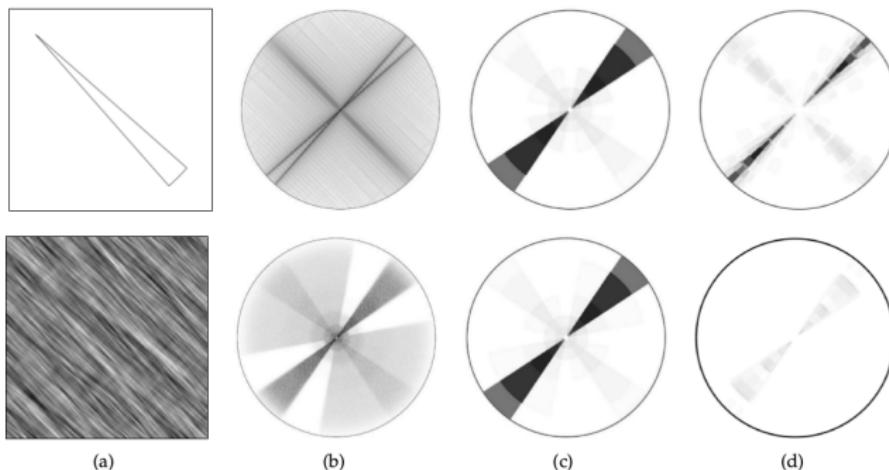


FIGURE 4: Visualization of the scattering coefficients for  $m=1$  (left) and  $m=2$  (right)

## EXAMPLE OF THE SCATTERING COEFFICIENTS



**FIGURE 5:** Scattering display of two images having the same first order scattering coefficients. a) Image, b) Fourier modulus c) Coefficients with  $m=1$ , d) Coefficients with  $m=2$

# HYBRID SCATTERING NETWORKS

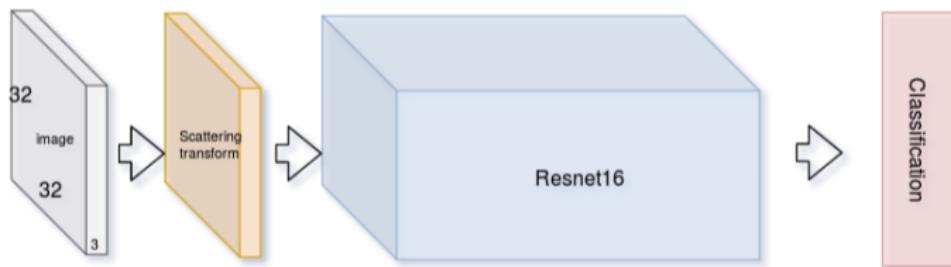


FIGURE 6: Architecture

Method	100	500	1000	Full
WRN 16-8	$34.7 \pm 0.8$	$46.5 \pm 1.4$	$60.0 \pm 1.8$	<b>95.7</b>
VGG 16 [58]	$25.5 \pm 2.7$	$46.2 \pm 2.6$	$56 \pm 1.0$	92.6
Scat + WRN	<b><math>38.9 \pm 1.2</math></b>	<b><math>54.7 \pm 0.6</math></b>	<b><math>62.0 \pm 1.1</math></b>	93.1

FIGURE 7: Results of 2017 paper

# DATASETS - KITTI

## KITTI

- ▶ Content: street and traffic scenes
- ▶ number of samples: 7480



(A)



(B)



(C)



(D)

# DATASETS - VOC

## VOC

- ▶ miscellaneous (singular) objects
- ▶ VOC2007 and VOC2012
- ▶ number of samples: 9963 + 17125



(E)

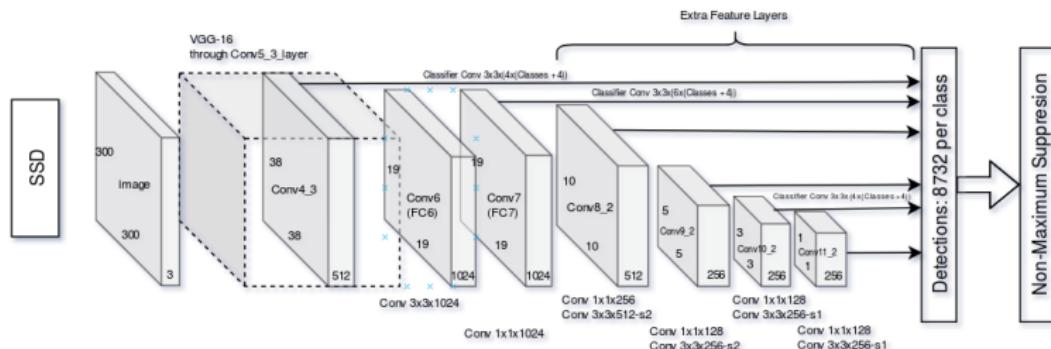


(F)



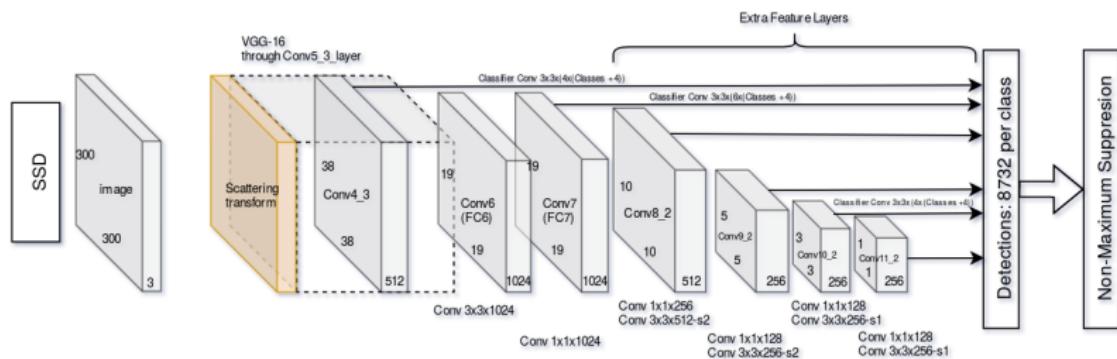
(G)

# SIMPLE SINGLE SHOT MULTIBOX DETECTOR (SSD)



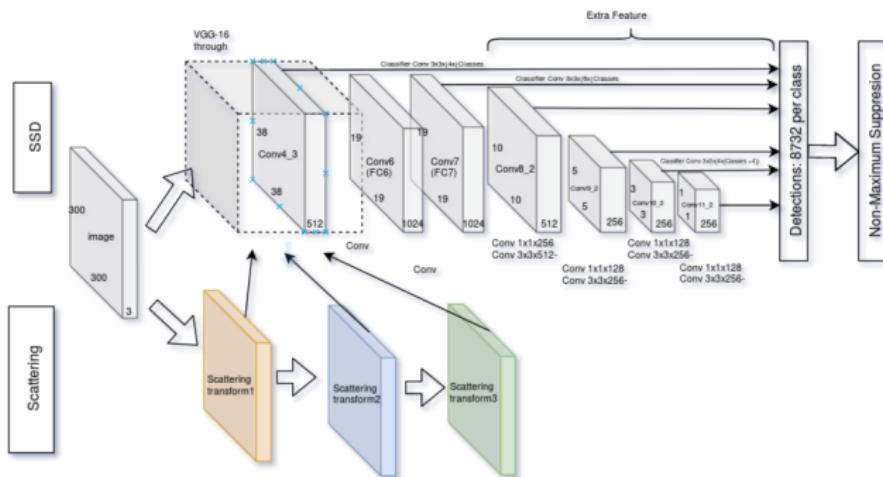
# SEQUENTIAL SCATTERING SSD

- ▶ Scattering is applied before data is piped through SSD



# CONTINUOUS FUSION SCATTERING SSD

- ▶ Data is piped through scattering and standard SSD and continuously merged at different stages



## FURTHERS PLANS AND ADDITIONAL IDEAS

- ▶ try to achieve same baseline as other SSD implementations on kitti did:  $\sim 50\%$
- ▶ use other base-architecture: faster RCNN, masked RCNN, ...
- ▶ integrate further datasets: COCO, FDDB, ...

## STATUS QUO IN PICTURES - KITTI

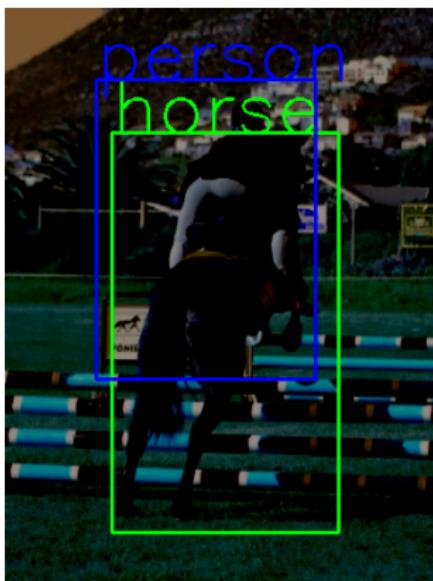


(H)

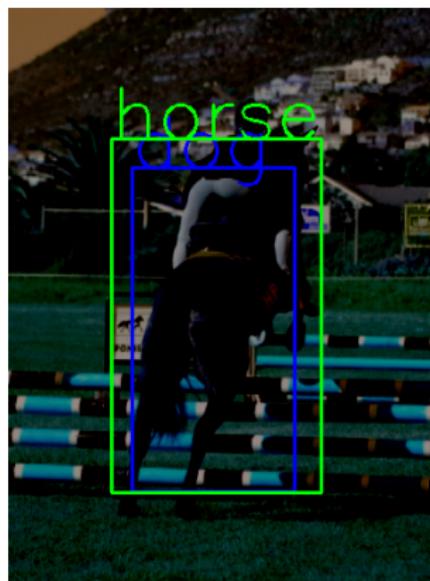


(I)

## STATUS QUO IN PICTURES - VOC + SCATTERING



(J)



(K)

# STATUS QUO IN NUMBERS

dataset	train accuracy	test accuracy
VOC	0.76	0.61
Kitti	0.82	0.12
kitti1000x300	-	0.05
Kitti small	0.95	0.0
Kitti small1000x300	0.95	0.0
Scattering Hybrid VOC	-	0.06

## QUESTIONS AND SUGGESTIONS

- ▶ Any questions?
- ▶ Any suggestions, tips, ... are very welcome

# REFERENCES

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