Sophia Sanborn VS265 Guest Lecture Fall 2020

# Computing Perceptual Invariants

# Outine

- 1. The problem of invariance
- 2. The mathematics of invariance
- 3. Invariance in visual cortex
- 4. Invariance in convolutional neural networks

### Computing Perceptual Invariants



# The Problem of Invariance



# The Problem of Invariance



### The Problem of Invariance



### The Problem of Invariance

VOL. IX.

#### ON THE FOUNDATIONS OF GEOMETRY.<sup>1</sup>

ALTHOUGH I have already had occasion to set forth my views A on the foundations of geometry,<sup>1</sup> it will not, perhaps, be unprofitable to revert to the question with new and ampler developments, and seek to clear up certain points which the reader may have found obscure. It is with reference to the definition of the point and the determination of the number of dimensions that new light appears to me most needed; but I deem it opportune, nevertheless, to take up the question from the beginning.

Our sensations cannot give us the notion of space. That notion is built up by the mind from elements which pre-exist in it, and external experience is simply the occasion for its exercising this power, or at most a means of determining the best mode of exercising it.

No. 1.

### THE MONIST

#### Henri Poincaré

#### SENSIBLE SPACE.





### ROTATIONS

### REFLECTIONS



Invariance

 $f(\phi(x)) = f(x)$ 

Invariance

 $f(\phi(x)) = f(x)$ 



Invariance

 $f(\phi(x)) = f(x)$ 



Equivariance  $f(\phi(x)) = \phi'(f(x))$ 

Invariance

 $f(\phi(x)) = f(x)$ 



### Equivariance $f(\phi(x)) = \phi'(f(x))$





Invariance

 $f(\phi(x)) = f(x)$ 



### Equivariance $f(\phi(x)) = \phi'(f(x))$

























$$f_n = \sum_{n=0}^{N-1} \hat{f}_{\omega} e^{\frac{i2\pi\omega n}{N}}$$





$$f_n = \sum_{n=0}^{N-1} \hat{f}_{\omega} e^{\frac{i2\pi\omega n}{N}}$$

















### **Top Fourier Coefficients**

### **Original Fourier Coefficients**



#### Fourier Coefficients of Shifted Signal



**Power Spectrum** 

 $P_{\omega} = |\hat{f}_{\omega}|^2$ 



Power Spectrum

20

10

0



Power Spectrum

20

10

0



Power Spectrum

10

0

### Simple Cells

![](_page_30_Figure_2.jpeg)

### **Complex Cells**

![](_page_30_Figure_4.jpeg)

![](_page_31_Picture_2.jpeg)

### **Quadrature Pair of Gabors**

![](_page_32_Picture_2.jpeg)

![](_page_32_Picture_3.jpeg)

# The Energy Model **Quadrature Pair of Gabors**

![](_page_33_Picture_2.jpeg)

![](_page_33_Picture_3.jpeg)

![](_page_34_Picture_1.jpeg)

### **Bispectrum**

 $\beta(f)_{j,k} = \hat{f}_j^* \hat{f}_k^* \hat{f}_{j+k}$ 

 $\beta(f)_{j,k} = \left(\sum_{t=0}^{\tau} e^{i2\pi t j/\tau} f_t\right) \left(\sum_{t=0}^{\tau} e^{i2\pi x k/\tau} f_t\right) \left(\sum_{t=0}^{\tau} e^{-i2\pi t (j+k)/\tau} f_t\right)$ 

#### **Bispectrum**

 $\beta(f)_{j,k} = \hat{f}_{i}^{*} \hat{f}_{k}^{*} \hat{f}_{j+k}$ 

![](_page_37_Figure_1.jpeg)

![](_page_37_Figure_2.jpeg)

![](_page_37_Figure_4.jpeg)

![](_page_37_Picture_5.jpeg)

![](_page_38_Figure_1.jpeg)

### Convolution

![](_page_39_Figure_2.jpeg)

### Pooling

![](_page_39_Figure_4.jpeg)

#### Convolution

![](_page_40_Figure_2.jpeg)

### Equivariance

to translation within the global image plane

### Pooling

![](_page_40_Figure_6.jpeg)

#### Convolution

![](_page_41_Figure_2.jpeg)

### Equivariance

to translation within the global image plane

![](_page_41_Figure_5.jpeg)

#### Convolution

![](_page_42_Figure_2.jpeg)

### Equivariance

to translation within the global image plane

### Pooling

![](_page_42_Figure_6.jpeg)

#### Invariance

to slight perturbations within a local region

#### Translation

![](_page_43_Figure_2.jpeg)

#### Rotation

![](_page_43_Figure_4.jpeg)

### Max Pooling

![](_page_44_Figure_2.jpeg)

### **Data Augmentation**

![](_page_45_Picture_2.jpeg)

![](_page_46_Figure_1.jpeg)

![](_page_47_Figure_1.jpeg)

![](_page_47_Figure_2.jpeg)

![](_page_47_Figure_3.jpeg)

![](_page_48_Figure_1.jpeg)

All neurons in the previous layer with at least 30% of the max weight magnitude are shown, both **positive** (excitation) and negative (inhibition). Click on a neuron to see its forwards and backwards weights.

![](_page_48_Figure_3.jpeg)

#### **Color Contrast** 16%

![](_page_49_Picture_2.jpeg)

#### **Complex Gabor** 14%

![](_page_49_Picture_4.jpeg)

![](_page_49_Figure_5.jpeg)

#### **Low Frequency** 27%

![](_page_49_Picture_7.jpeg)

![](_page_49_Figure_8.jpeg)

![](_page_49_Picture_9.jpeg)

![](_page_50_Picture_1.jpeg)

![](_page_50_Figure_2.jpeg)

#### Angles 3%

![](_page_51_Picture_2.jpeg)

![](_page_51_Picture_3.jpeg)

![](_page_51_Picture_4.jpeg)

![](_page_51_Picture_5.jpeg)

![](_page_51_Picture_7.jpeg)

#### **Repeating patterns** 5%

![](_page_51_Picture_9.jpeg)

![](_page_51_Picture_11.jpeg)

![](_page_51_Figure_12.jpeg)

![](_page_51_Picture_13.jpeg)

![](_page_51_Picture_14.jpeg)

![](_page_52_Picture_1.jpeg)

![](_page_52_Picture_2.jpeg)

![](_page_52_Picture_3.jpeg)

![](_page_52_Picture_4.jpeg)

![](_page_52_Picture_5.jpeg)

![](_page_52_Figure_6.jpeg)

![](_page_52_Picture_7.jpeg)

InceptionV1 has a left-oriented pathway detecting dogs facing left...

#### ... and a symmetric right-oriented pathway detecting dogs facing right. At each step, the two pathways **inhibit** each other and excite the next stage.

![](_page_53_Picture_3.jpeg)

![](_page_53_Picture_4.jpeg)

![](_page_53_Picture_5.jpeg)

#### **Oriented Heads** (4a)

![](_page_53_Picture_7.jpeg)

![](_page_53_Picture_8.jpeg)

![](_page_53_Picture_9.jpeg)

Union over left and right cases.

Union over left and right cases.

#### **Orientation-Invariant Head** (4b)

![](_page_53_Picture_13.jpeg)

#### **Orientation-Invariant Head+Neck** (4c)

![](_page_53_Picture_15.jpeg)

![](_page_53_Picture_16.jpeg)

![](_page_53_Picture_17.jpeg)

### **Too Invariant?**

![](_page_54_Picture_1.jpeg)

### Not Invariant Enough?

![](_page_55_Picture_1.jpeg)

Original image Temple (97%)

![](_page_55_Picture_4.jpeg)

Perturbations

![](_page_55_Picture_6.jpeg)

Adversarial example

Ostrich (98%)