### Factored 3-Way Restricted Boltzmann Machines for Modeling Natural Images

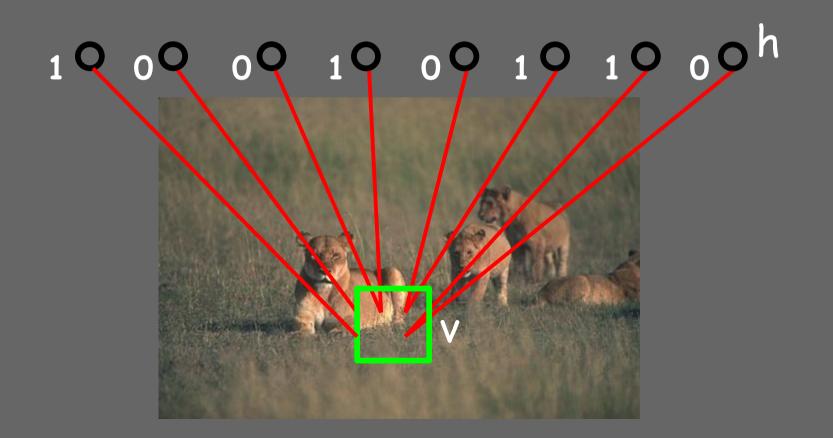
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AISTATS - 14 May 2010

Want to model natural images by using a generative model p(image v; W)

Want to use the model to produce representations p(image v, hidden units h; W)



Goal: define p(v, h)

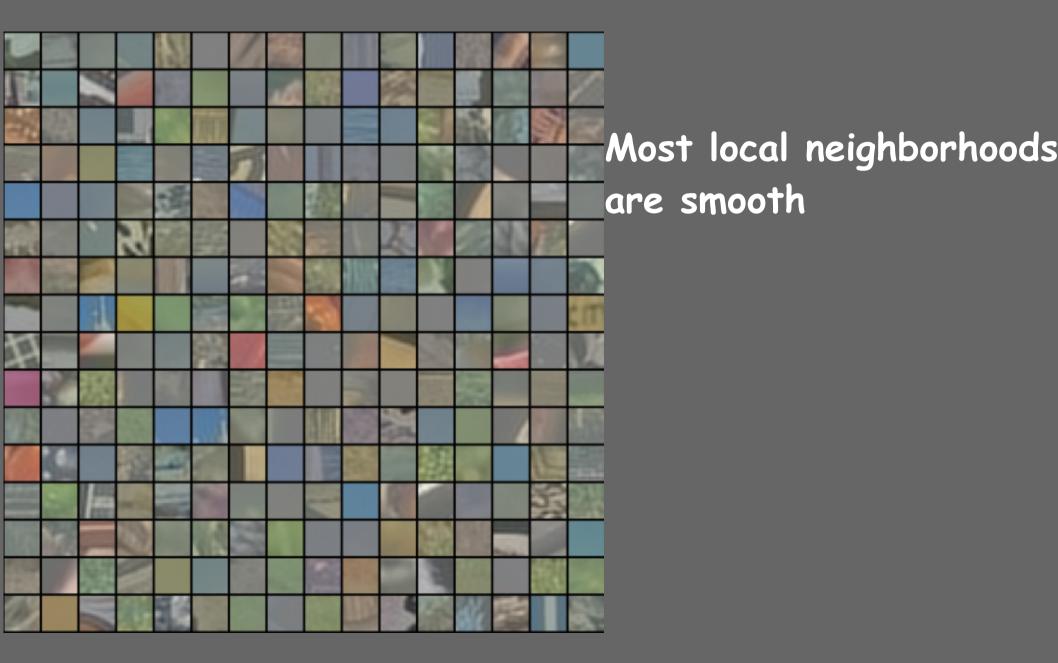
### Q.: What is the key property of natural images?

Goal: define p(v, h)

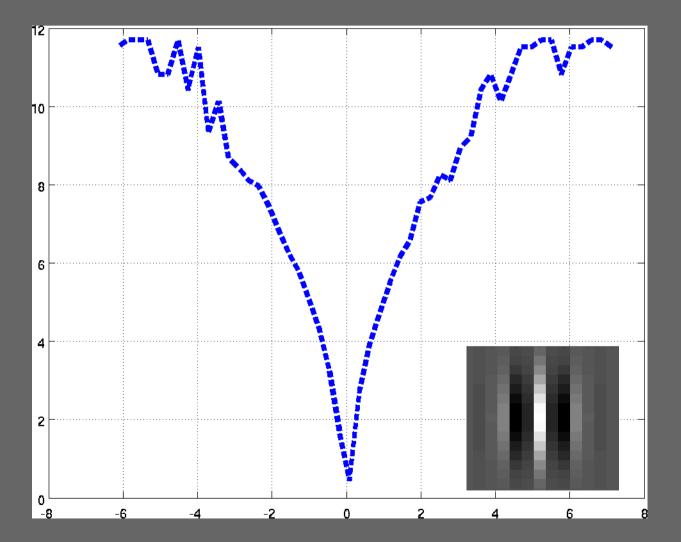
Q.: What is the key property of natural images?A.: smoothness

#### $v_1 v_2 v_3$ **O O O**

Most of the times, the value of one pixel can be well predicted from its neighbors

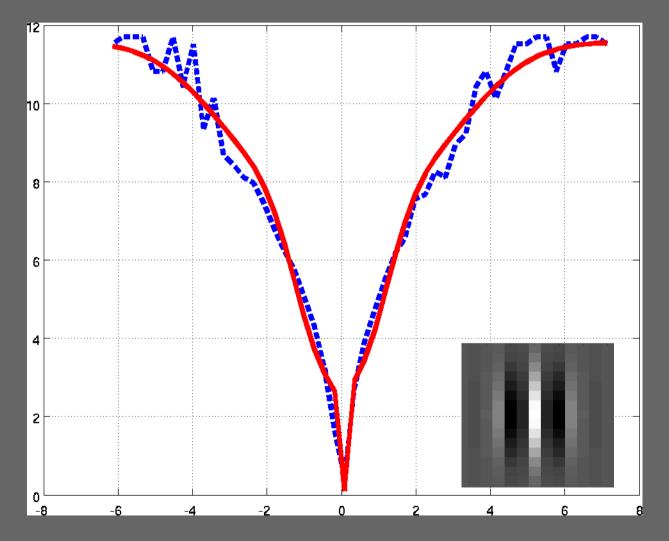


### - log( empirical p.d.f. of filter response) )



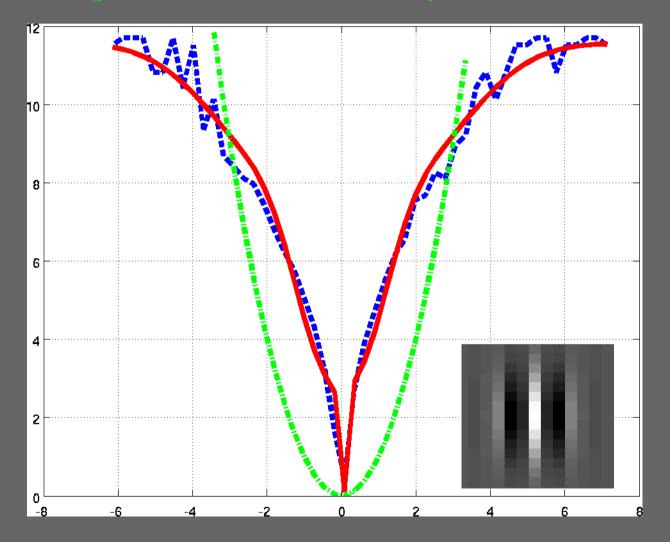
Finding an edge at this location and orientation is rare

- log( empirical p.d.f. of filter response) )
- log( fit of model p.d.f. to filter response) )



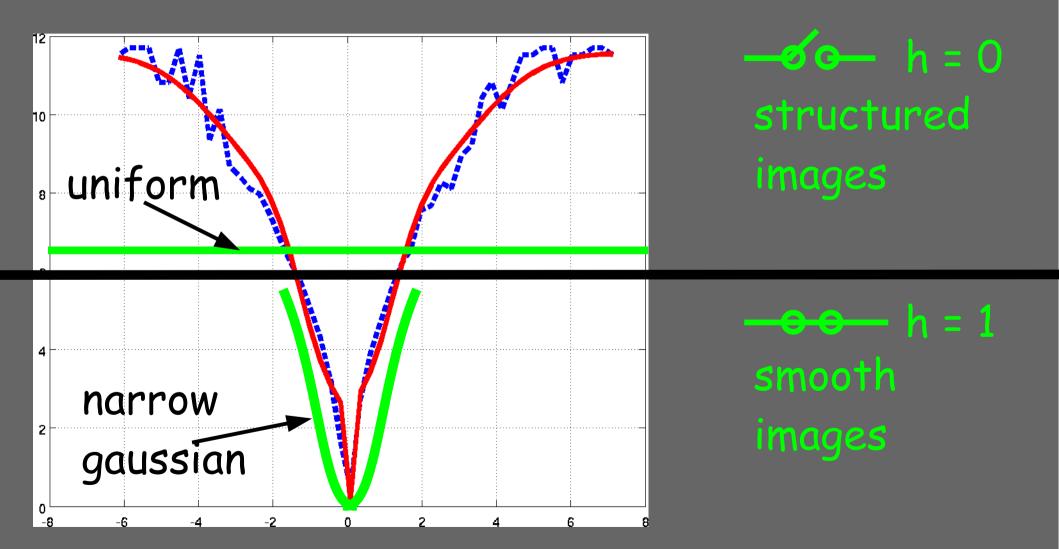
Finding an edge at this location and orientation is rare

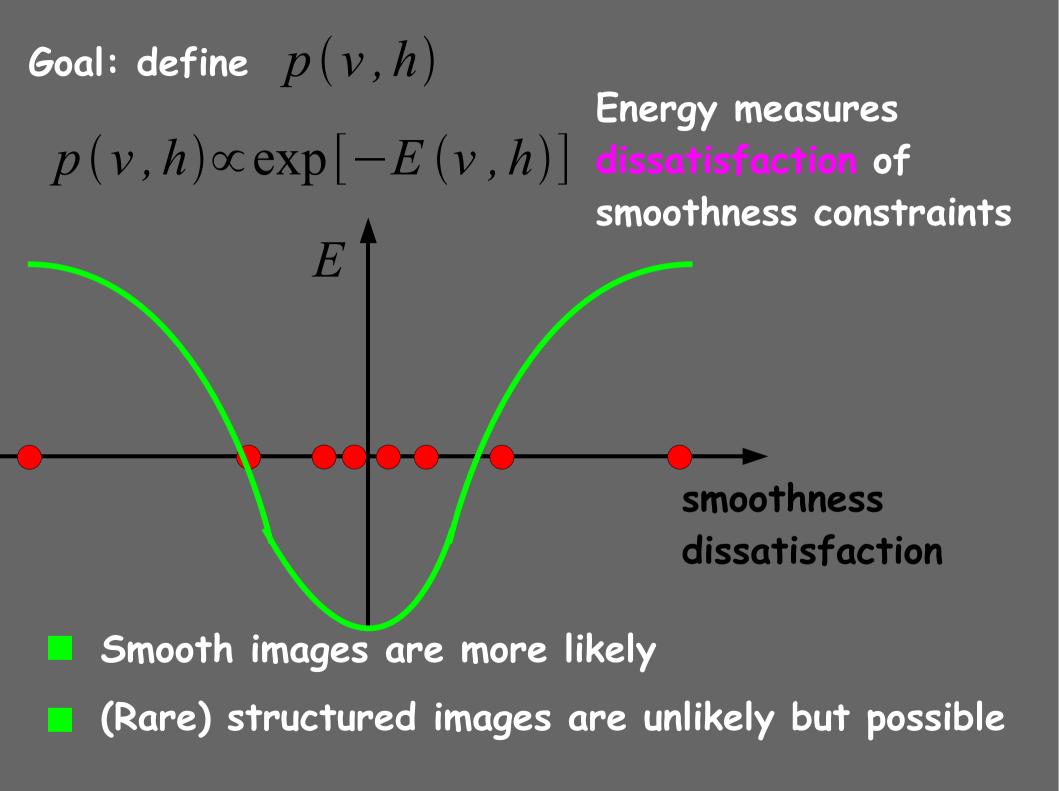
- log( empirical p.d.f. of filter response) )
- log( fit of model p.d.f. to filter response) )
- log( fit of Gaussian p.d.f. to filter response) )

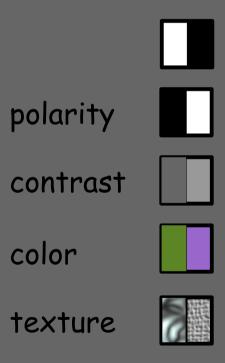


Finding an edge at this location and orientation is rare

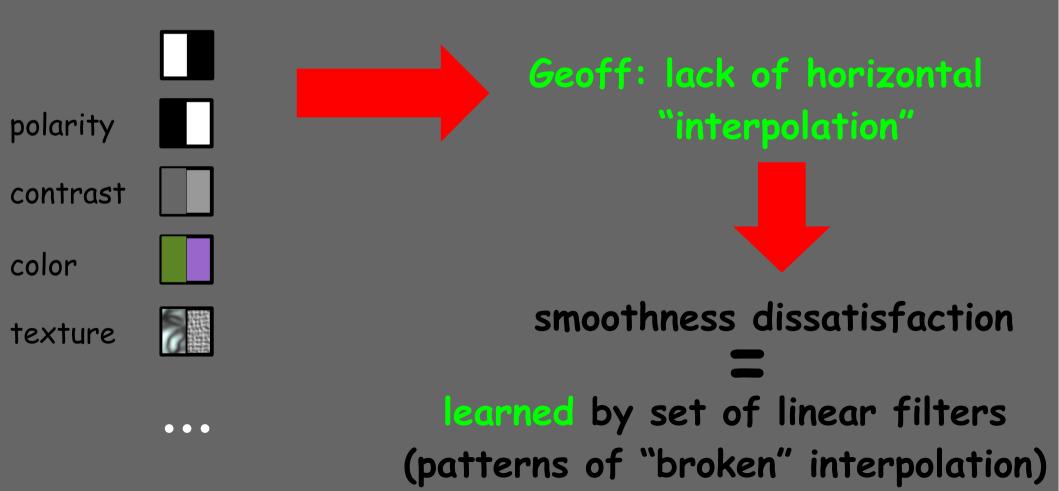
### KEY IDEA: use "<u>switch</u>" hidden variable









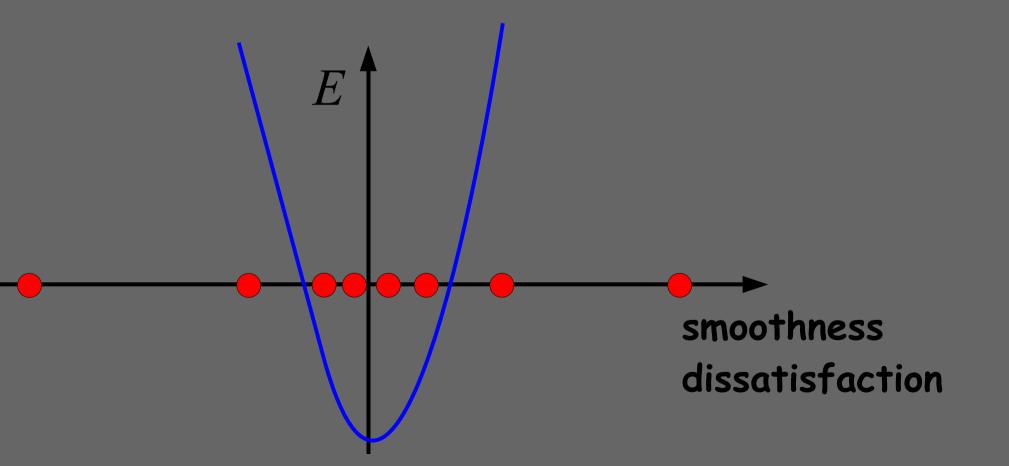


# $E = \sum_{i}$ smoothness\_dissatisfaction $\begin{bmatrix} i \\ i \end{bmatrix} - b_{i}$

smoothness\_dissatisfaction  $_{i} = W_{i}v$ 

# $E = \sum_{i}$ smoothness\_dissatisfaction $_{i}^{2} - b_{i}$

smoothness\_dissatisfaction  $_{i} = W_{i}v$ 



## $E = \sum_{i} h_{i}$ smoothness\_dissatisfaction $_{i}^{2} - h_{i} b_{i}$

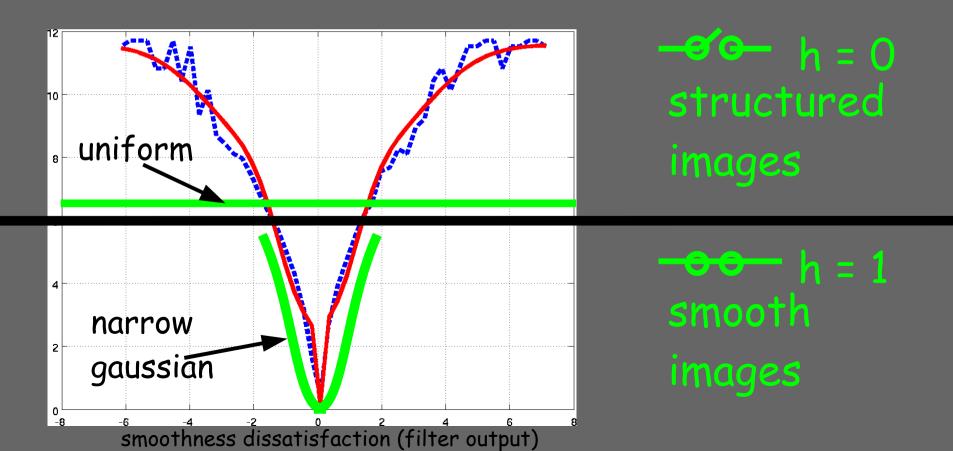
smoothness\_dissatisfaction  $_{i} = W_{i}v$ 

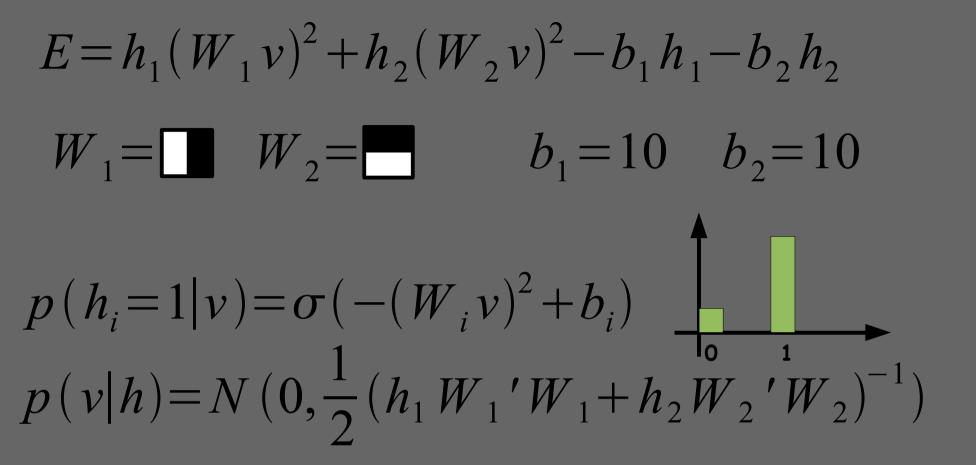
 $h_i \in \{0, \Omega\}$  introduce hiddens to allow violations

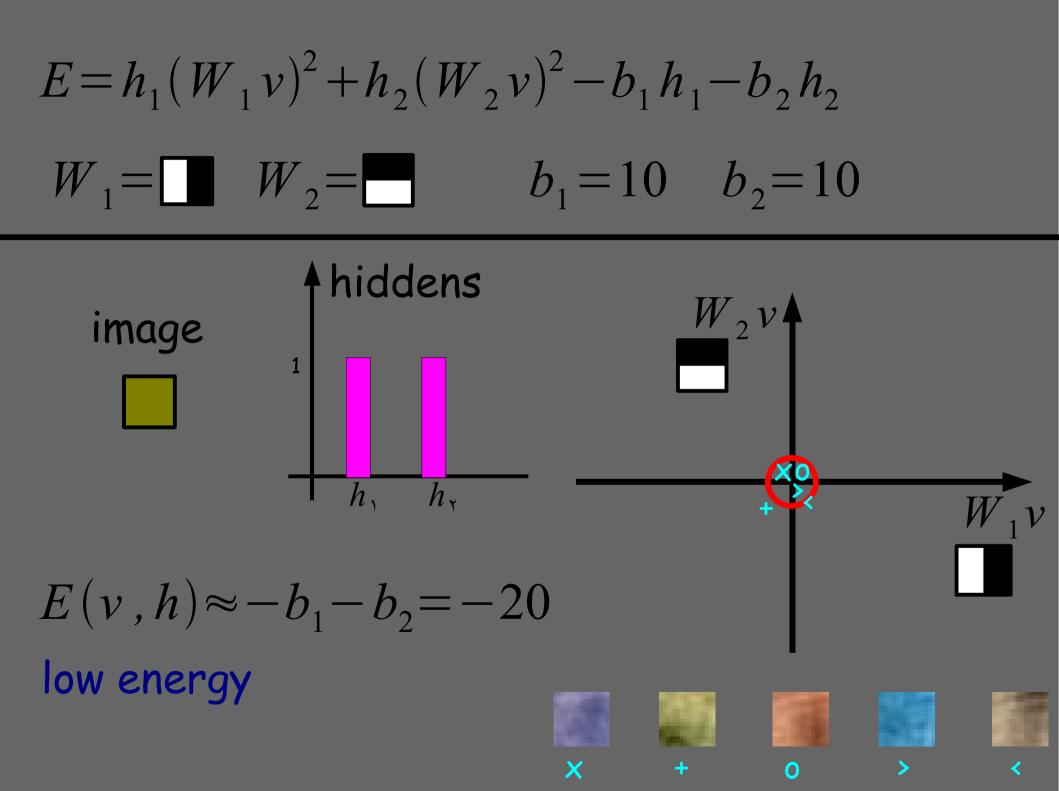
$$E = \sum_{i} h_{i}$$
 smoothness\_dissatisfaction $_{i}^{2} - h_{i} b_{i}$ 

smoothness\_dissatisfaction  $_{i} = W_{i}v$ 

 $h_i \in \{0,1\}$  introduce hiddens to allow violations

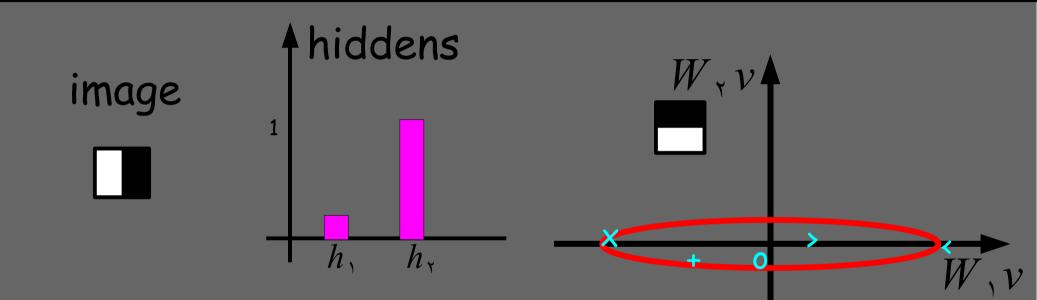






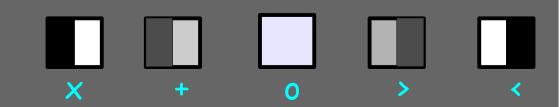
$$E = h_{,}(W,v)^{'} + h_{,}(W,v)^{'} - b_{,}h_{,} - b_{,}h_{,}$$

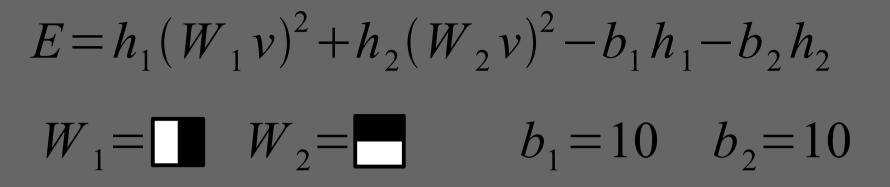
 $W_{\gamma} = \begin{bmatrix} W_{\gamma} = \end{bmatrix} \quad b_{\gamma} = \because \quad b_{\gamma} = \lor$ 



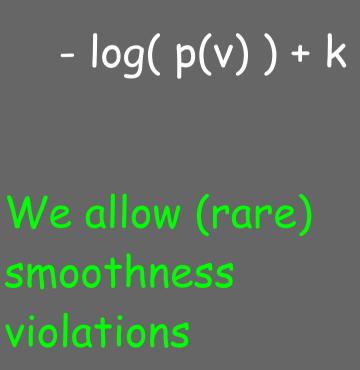
$$E(v,h) \approx -b_{\tau} = -1$$

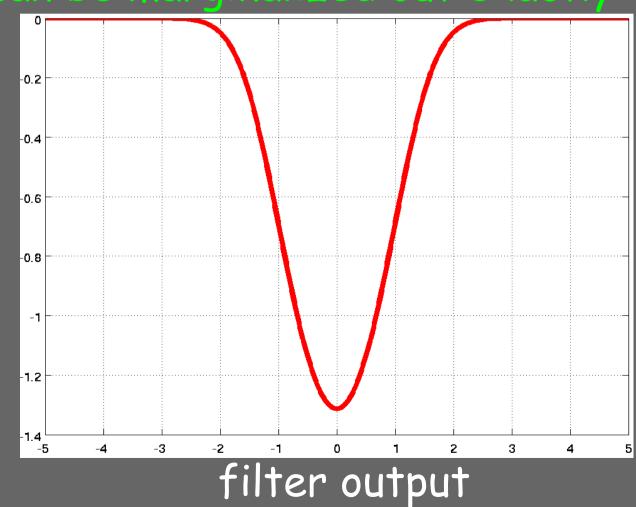
higher energy  $(h_1 \text{ gave discount!})$ 





### Binary hiddens can be marginalized out exactly



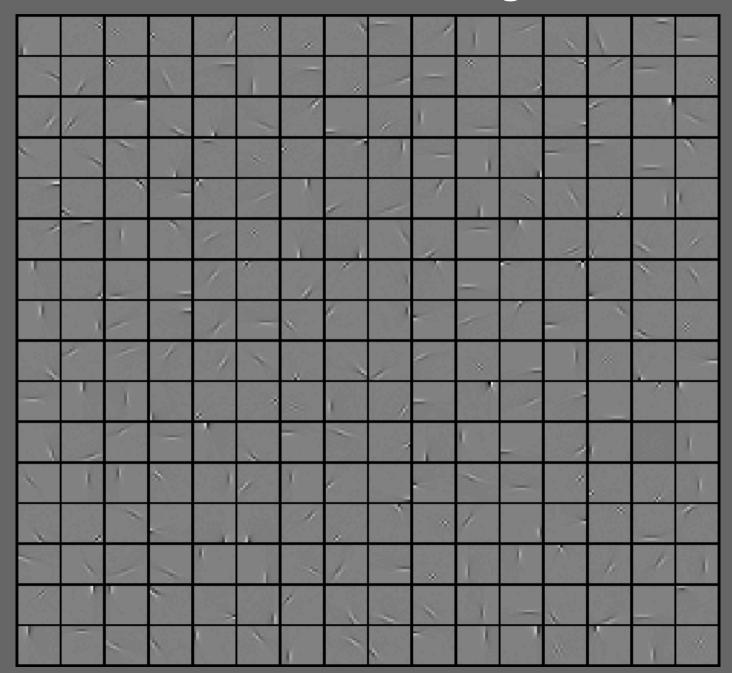


# $E = \frac{1}{2} \sum_{k} \sum_{f} h_{k} P_{fk} (W_{f} v)^{2} - b_{k} h_{k}$

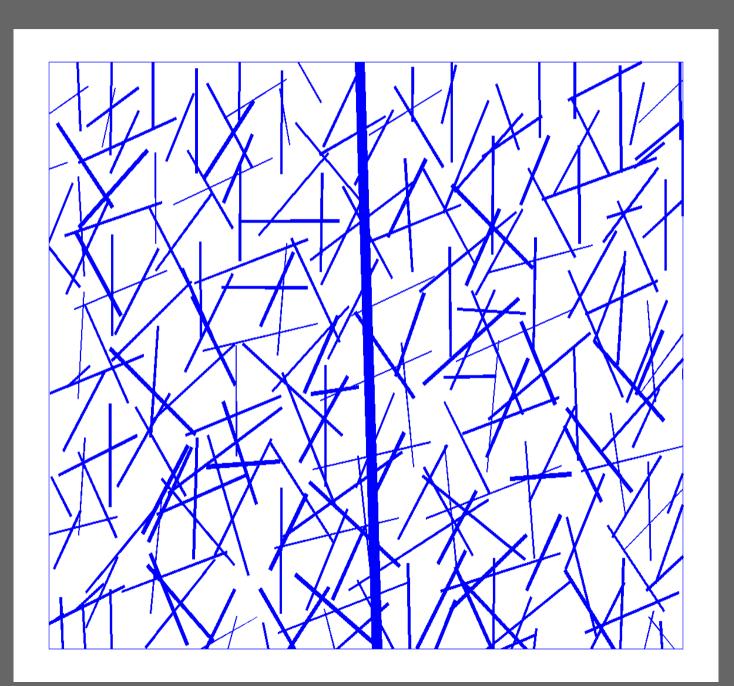
### Learning: $\{W, P, b\}$

- approximate maximum likelihood
  - Contrastive Divergence
  - Hybrid Monte Carlo

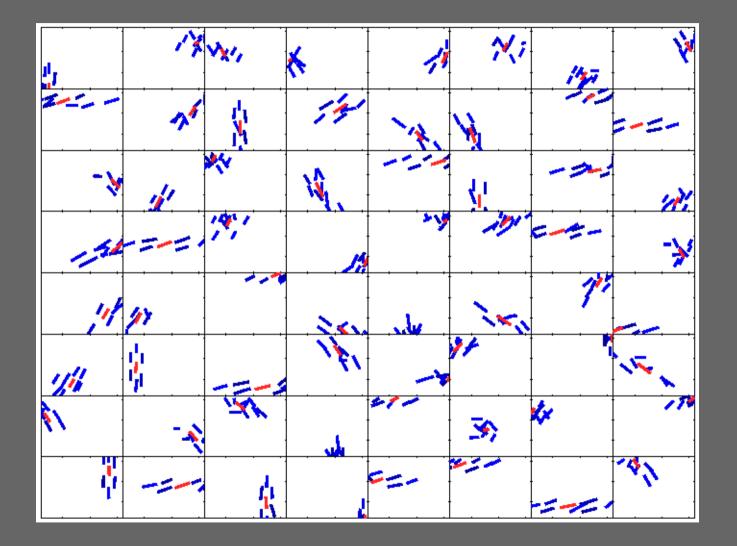
# Learned filters (directions of smoothness dissatisfaction) on natural images



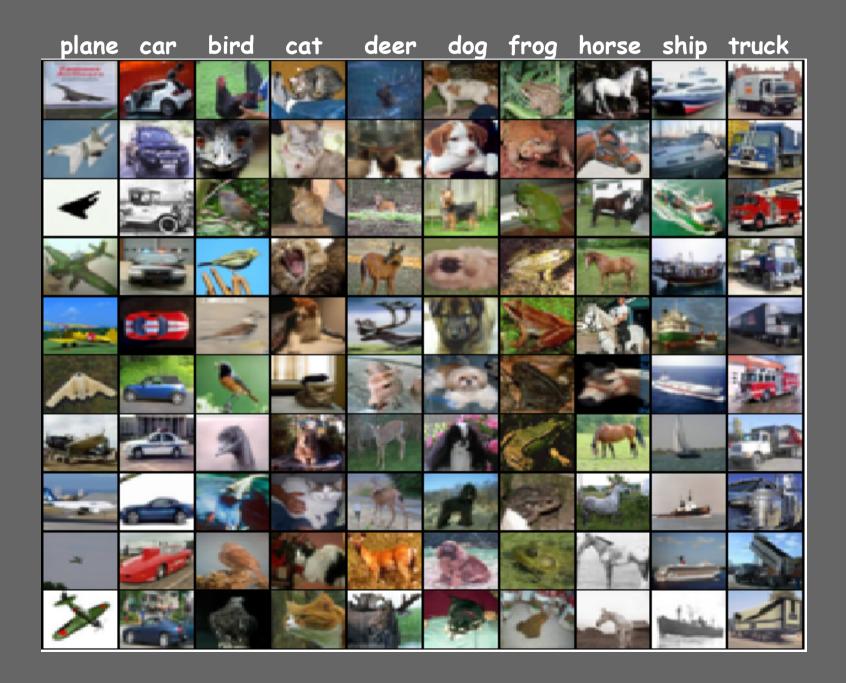
### Learned filters: Gabor fit



### Learned filters: grouping



### **RECOGNITION: CIFAR 10 dataset**



### RECOGNITION: CIFAR 10 dataset

	Accuracy
<mark>3way RBM - DBN</mark> input -> 9800 - 4096	64.7%
GRBM - DBN* input - 10000 - 10000	56.6%
<mark>3way RBM - DBN</mark> input -> 9800 - 4096 - 384	58.7%
GIST input - 384	54.7%

\* from Krizhevsky 2009

### Conclusions

Model of natural images producing binary features
Invariance or robustness to distortions
Good for recognition
Probabilistic model of simple-complex cell model
Easy to integrate with DBN's

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Code and more recent developments available at: http://www.cs.toronto.edu/~ranzato

