

# Unsupervised Learning

By Andrew Ng

기초 1팀

## Reference

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### **Bay Area Vision Meeting: Unsupervised Feature Learning and Deep Learning**

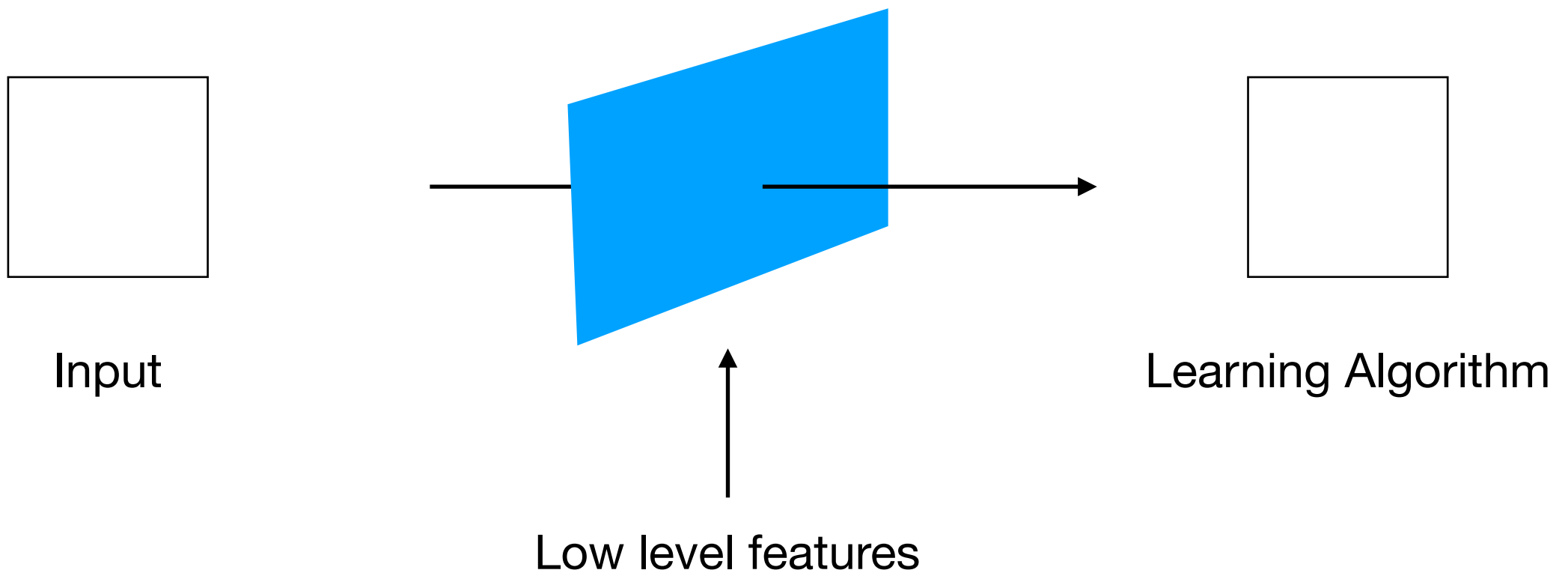
<https://www.youtube.com/watch?v=ZmNOAtZlgIk&t=1833s>

### **Neural networks [8.1] : Sparse coding - definition**

[https://www.youtube.com/watch?v=7a0\\_iEruGoM&t=5s](https://www.youtube.com/watch?v=7a0_iEruGoM&t=5s)

# Feature extraction

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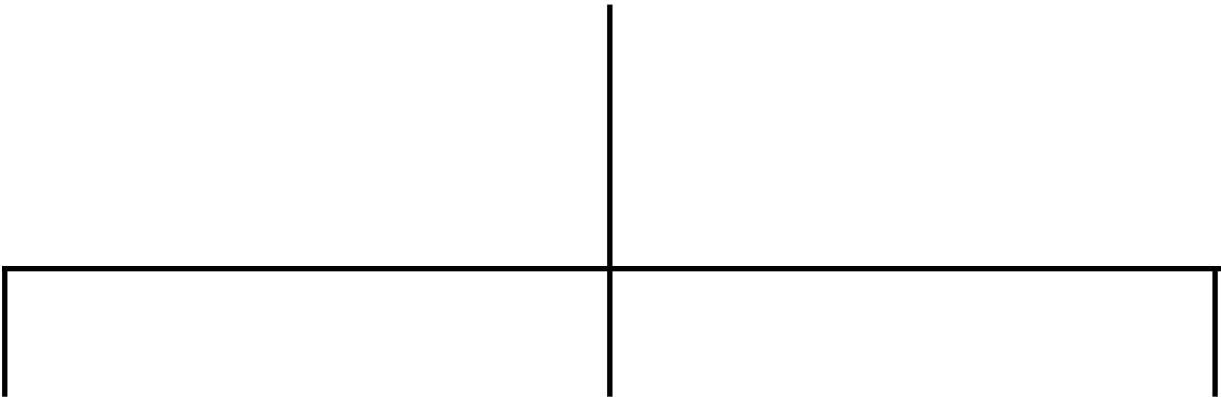


“알고리즘이 세상을 보는 렌즈”

**Low level feature**



Low level features



Object Detection

Audio Classification

NLP  
(자연 언어 처리)

There are some issues..

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14 x 14  
image patch

can represent it using  
**196**  
real numbers

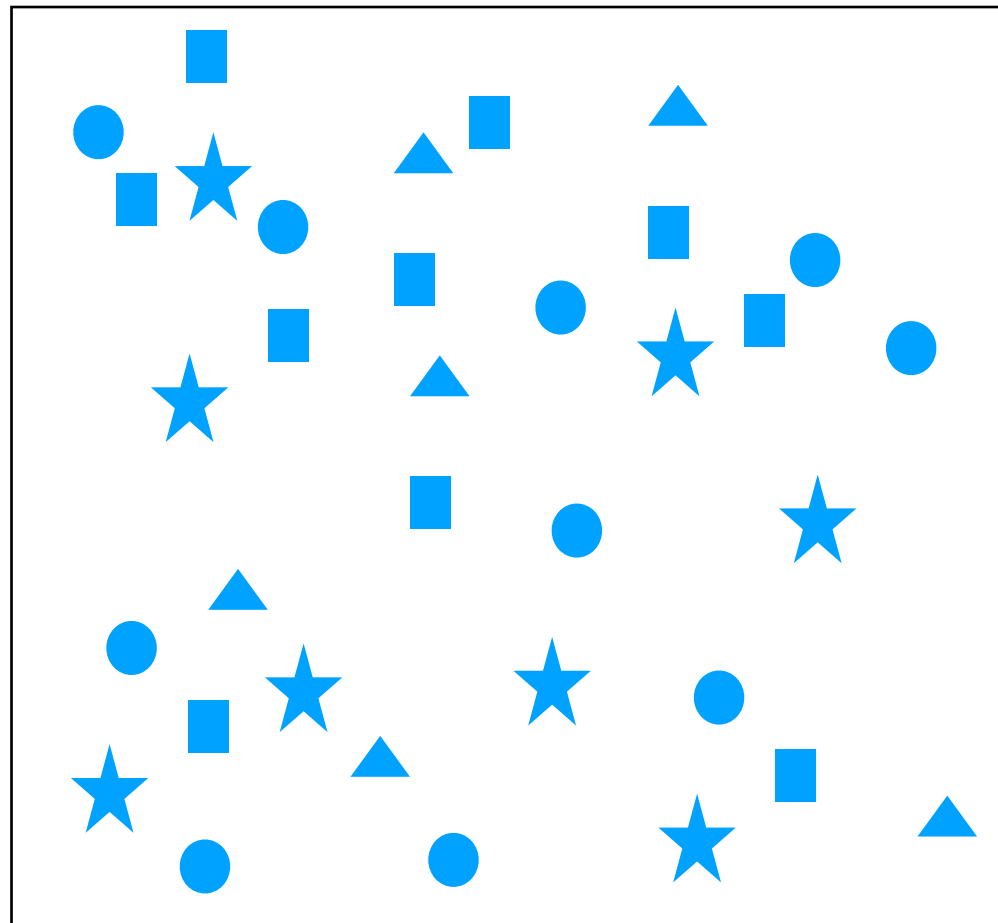
→

Can we find a learn a better feature vector  
to represent this?

# Unsupervised Learning

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UnSupervised Learning  
(Self-thought learning)



What is this?



## Sparse coding : one of neural networks for unsupervised learning

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# SPARSE CODING

### Topics: sparse coding

- For each  $\mathbf{x}^{(t)}$  find a latent representation  $\mathbf{h}^{(t)}$  such that:
  - ▶ it is sparse: the vector  $\mathbf{h}^{(t)}$  has many zeros
  - ▶ we can reconstruct the original input  $\mathbf{x}^{(t)}$  as well as possible

- More formally:

$$\min_{\mathbf{D}} \frac{1}{T} \sum_{t=1}^T \min_{\mathbf{h}^{(t)}} \frac{1}{2} \underbrace{\|\mathbf{x}^{(t)} - \mathbf{D} \mathbf{h}^{(t)}\|_2^2}_{\text{reconstruction error}} + \underbrace{\lambda \|\mathbf{h}^{(t)}\|_1}_{\text{sparsity penalty}}$$

reconstruction  $\hat{\mathbf{x}}^{(t)}$       reconstruction vs. sparsity control

- ▶ we also constrain the columns of  $\mathbf{D}$  to be of norm 1
  - otherwise,  $\mathbf{D}$  could grow big while  $\mathbf{h}^{(t)}$  becomes small to satisfy the prior
- ▶ sometimes the columns are constrained to be no greater than 1

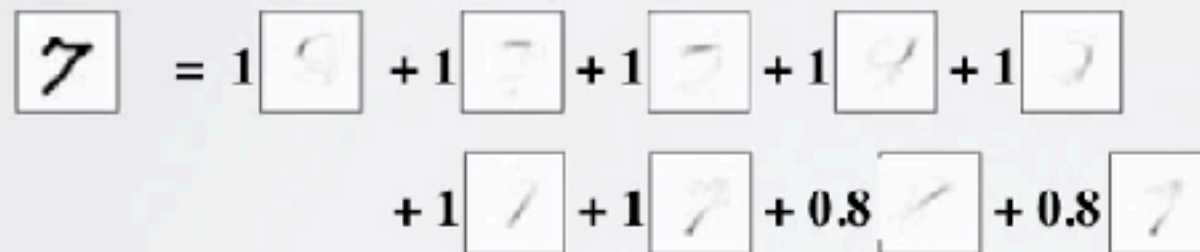
# Sparse coding

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## SPARSE CODING

**Topics:** dictionary

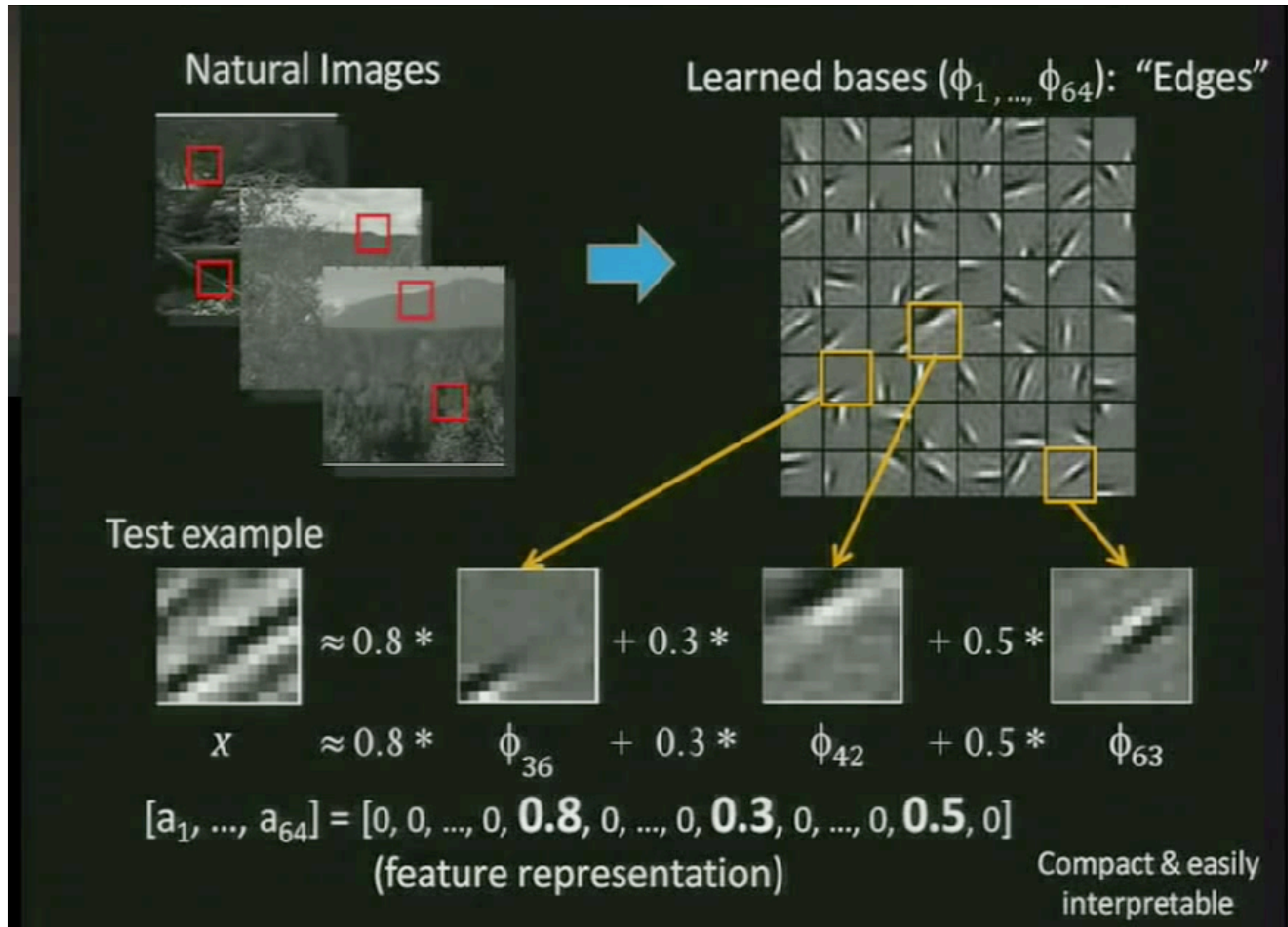
- Can also write  $\hat{\mathbf{x}}^{(t)} = \mathbf{D} \mathbf{h}(\mathbf{x}^{(t)}) = \sum_{\substack{k \text{ s.t.} \\ h(\mathbf{x}^{(t)})_k \neq 0}} \mathbf{D}_{:,k} h(\mathbf{x}^{(t)})_k$


$$\boxed{7} = 1 \boxed{9} + 1 \boxed{7} + 1 \boxed{2} + 1 \boxed{4} + 1 \boxed{3} + 1 \boxed{1} + 1 \boxed{7} + 0.8 \boxed{7} + 0.8 \boxed{7}$$

- ▶ we also refer to  $\mathbf{D}$  as the dictionary
  - in certain applications, we know what dictionary matrix to use
  - often however, we have to learn it



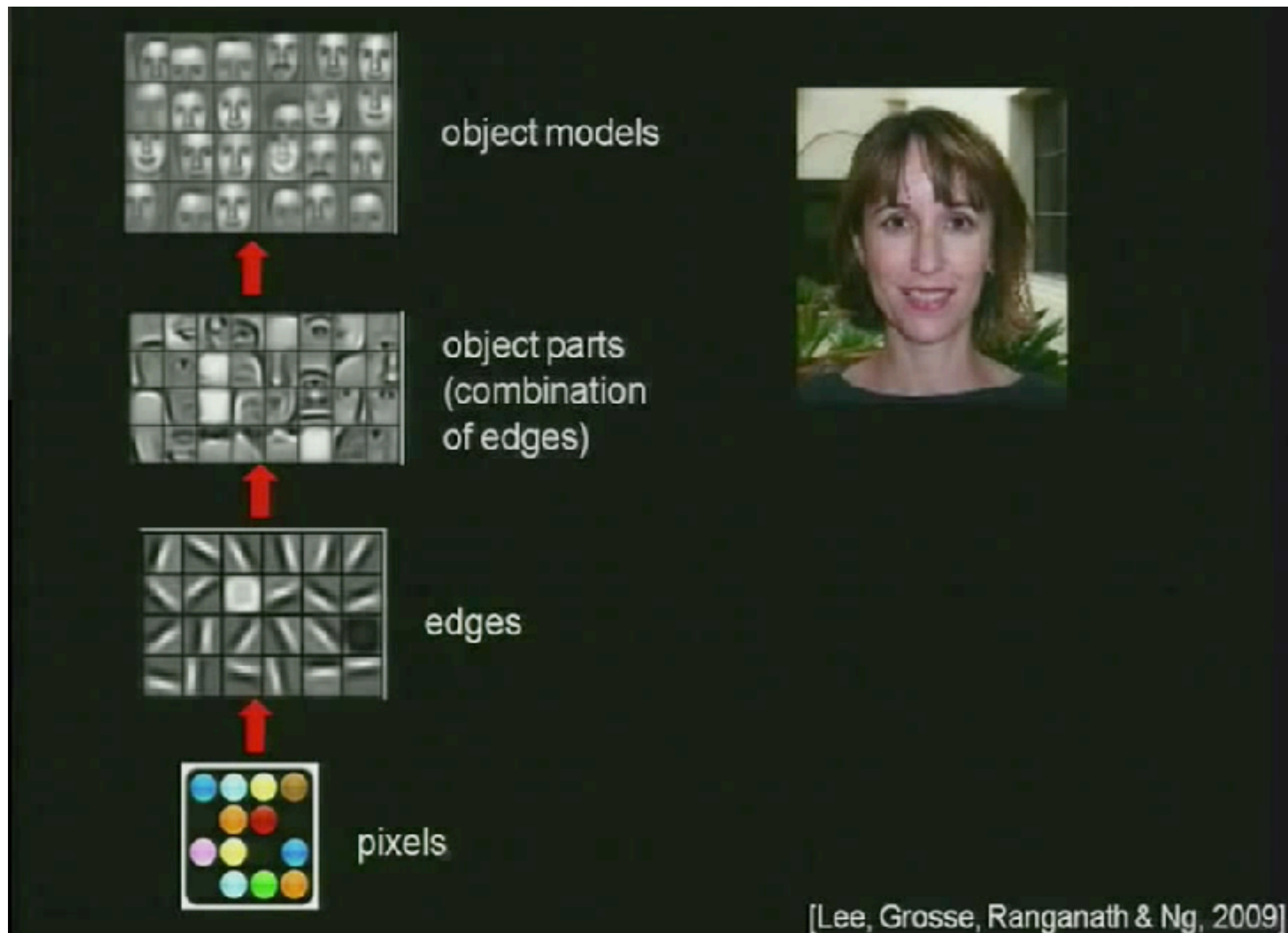
## Sparse coding



# Sparse DBN(Deep Learning Network)

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Training on face images

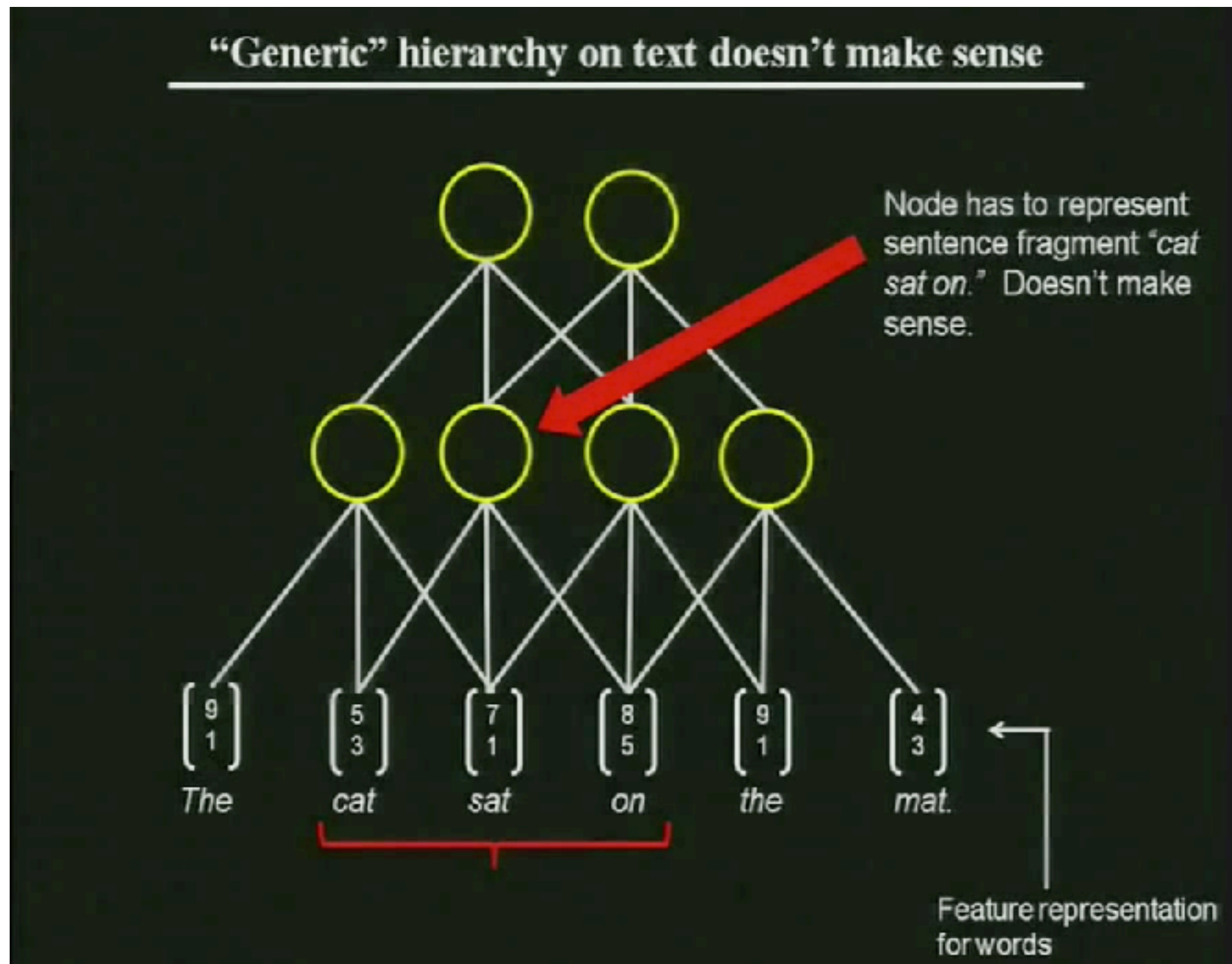


## Scaling up, Accuracy up

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- 효율적인 Sparse coding algorithms
- GPUs for 딥러닝
- Convolutional network
- ....

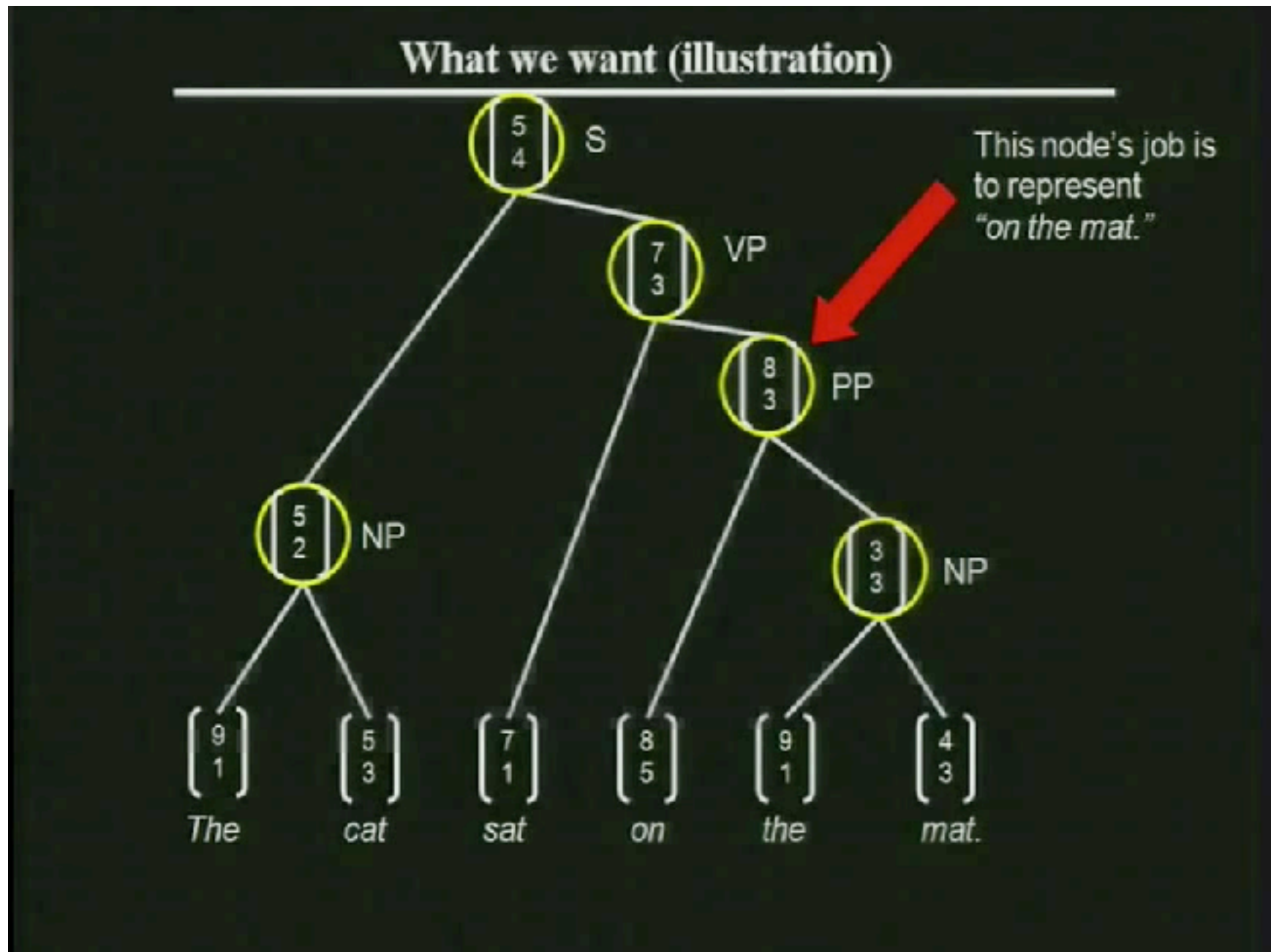
# Learning recursive representation





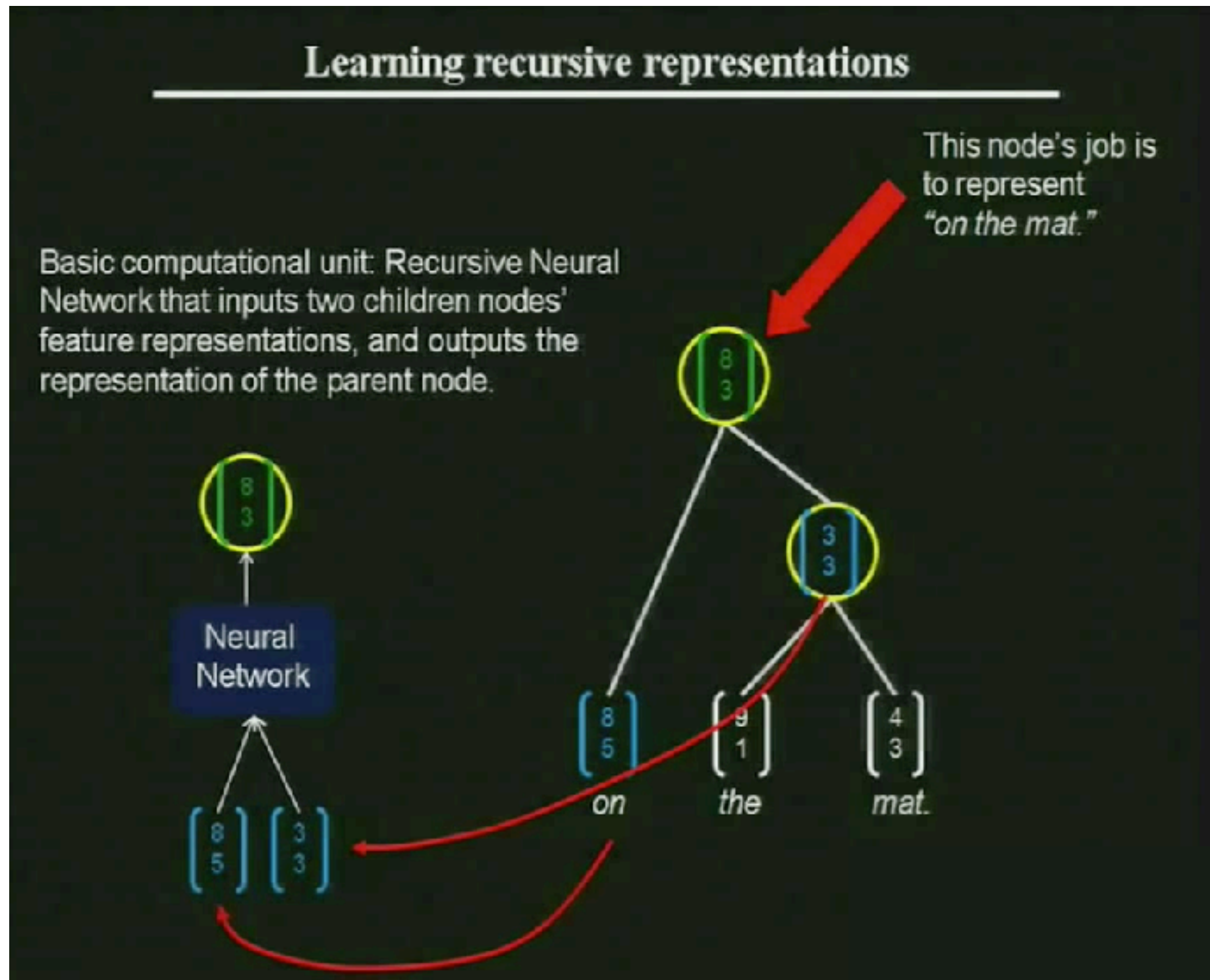
# Learning recursive representation

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learn to follow 'natural hierarchy' of English

# Learning recursive representation

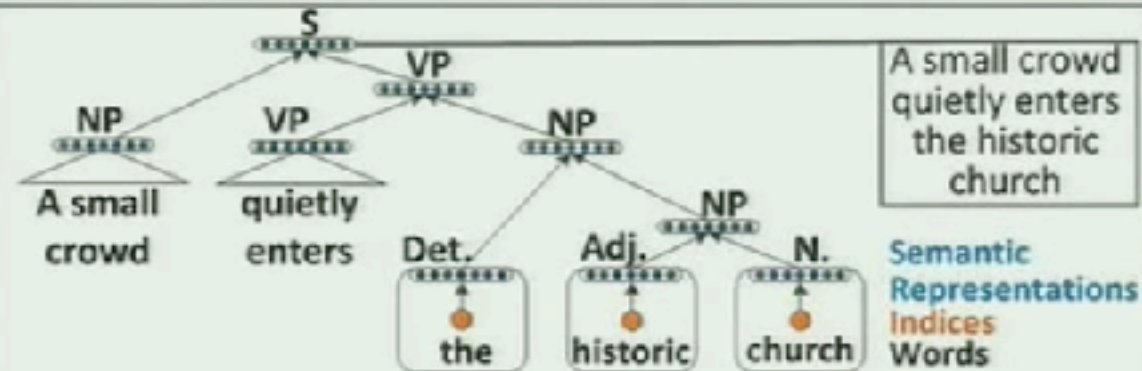


# Example

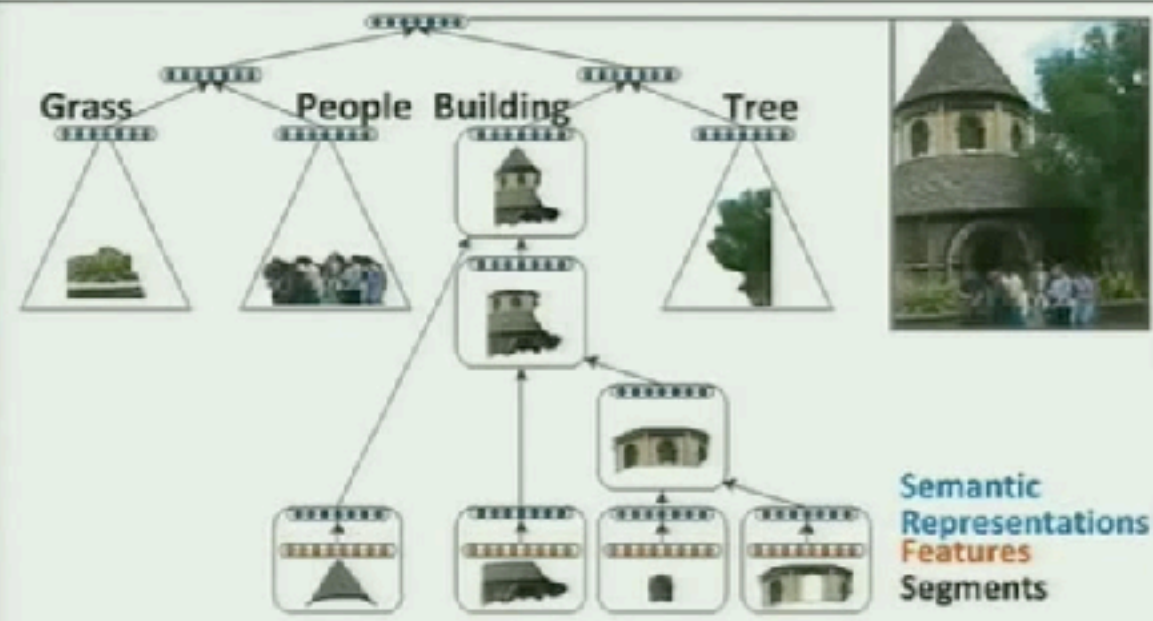
## Parsing sentences and parsing images

A small crowd  
quietly enters the  
historic church.

### Parsing Natural Language Sentences



### Parsing Natural Scene Images



Each node in the hierarchy has a "feature vector" representation.



## Example 2

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### Nearest neighbor examples for image patches

- Each node (e.g., set of merged superpixels) in the hierarchy has a feature vector.
- Select a node ("center patch") and list nearest neighbor nodes.
- I.e., what image patches/superpixels get mapped to similar features?



Selected patch

Nearest Neighbors