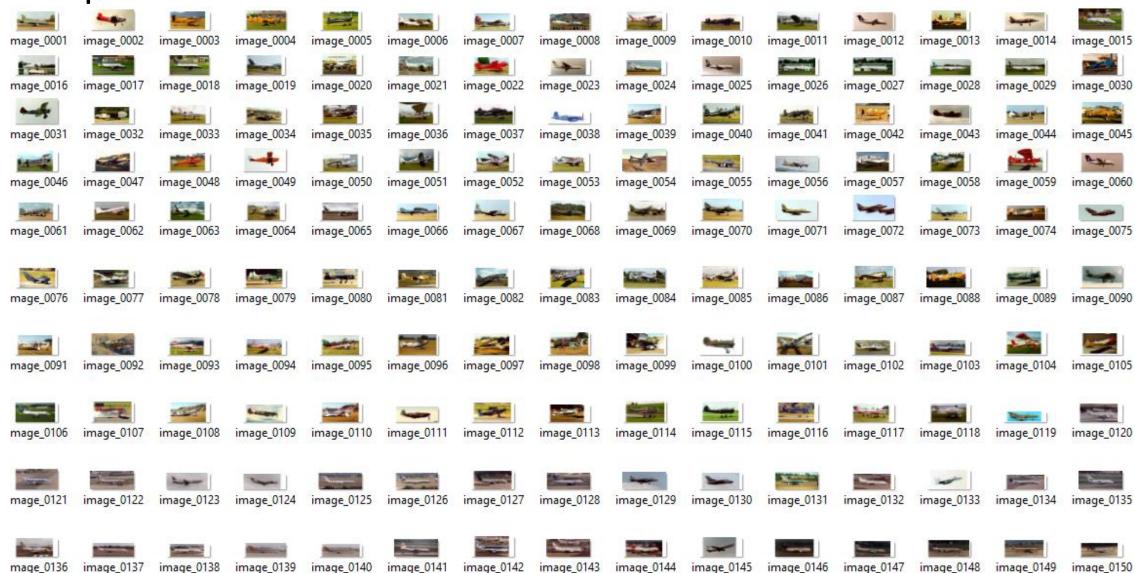
CSE463: Neural Networks

Visual Recognition: Revisit

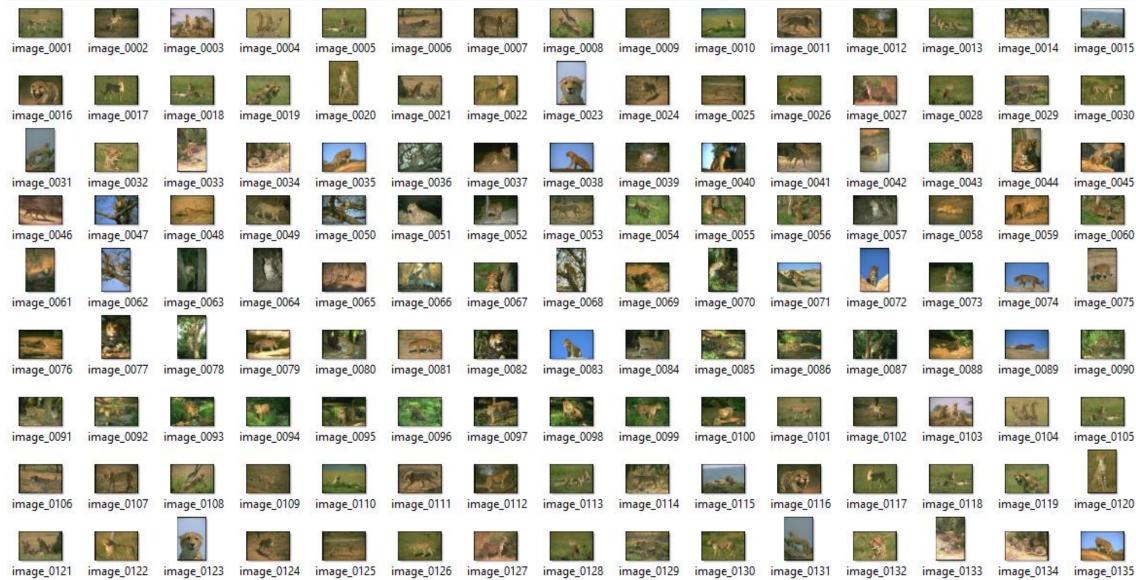
by:

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Computer & Systems Engineering Dept.,
Ain Shams University,
1 El-Sarayat Street, Abbassia, Cairo 11517

Airplane Class



Leopard Class



Motorbikes Class

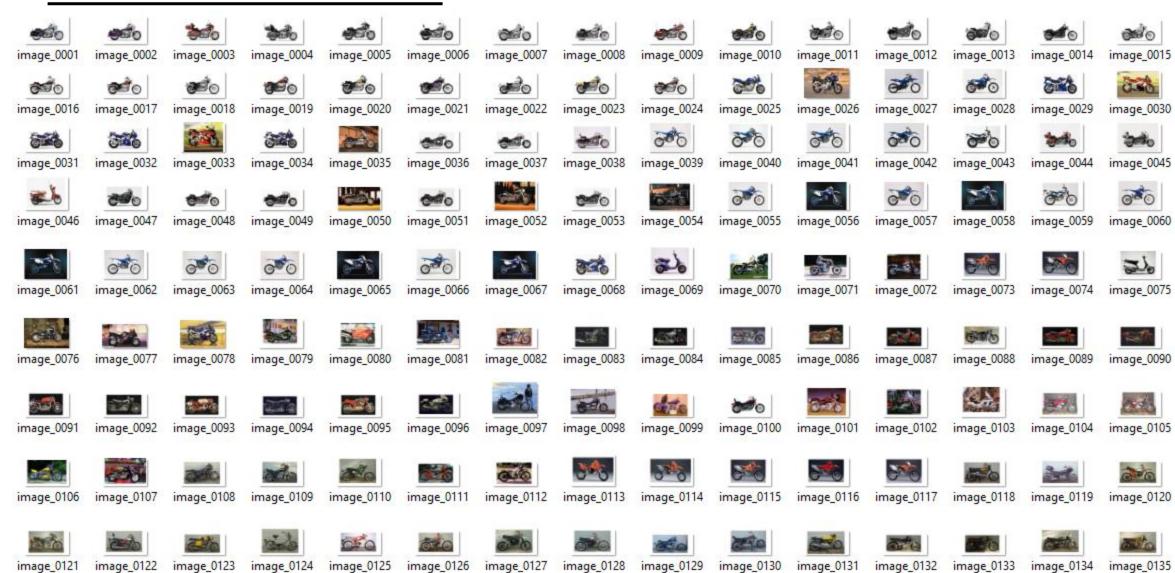


Image HoG Feature

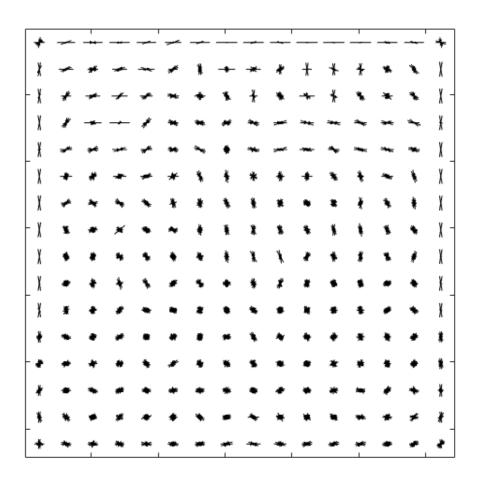
```
h=32; w=32;
NAirplanes=100;
s='airplanes//image ';
C1=[];
for i=1:NAirplanes
   [i]
   str=sprintf('%s%04d.jpg',s,i);
   im=imread(str);
   im=rgb2gray(im);
   im=imresize(im,[h w]);
   [hog,visualization] = extractHOGFeatures(im);
   subplot(1,2,1);imshow(im);
   subplot(1,2,2);plot(visualization);
   pause (0.1)
   C1(i,:)=hoq;
end
save('Airplanes.mat','C1')
```

HoG Feature Visualization



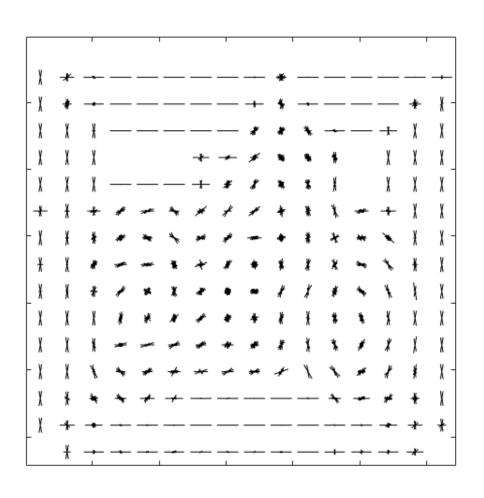
HoG Feature Visualization





HoG Feature Visualization





Class-i Score

$$S_i = f(X, W_i) = W_i.x$$

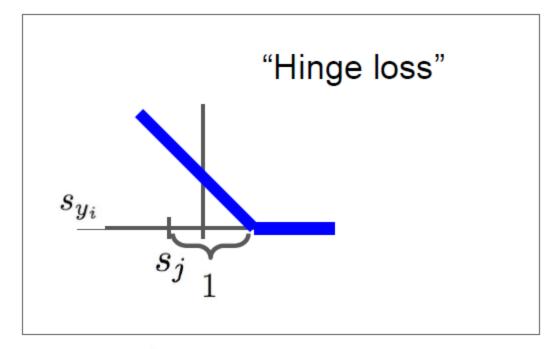






		Control of the Contro	
Airplane	<u>1.1320</u>	-0.4493	-0.4845
Leopard	-0.9674	0.6074	-0.3249
Motorbike	-0.1651	-0.1583	0.8091

Class-i Loss



$$L_i = \sum_{j \neq y_i} \begin{cases} 0 & \text{if } s_{y_i} \geq s_j + 1 \\ s_j - s_{y_i} + 1 & \text{otherwise} \end{cases}$$

= $\sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$

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1	1			1	ı
	E			1	1





cat

car

frog

Losses:

3.2

5.1

-1.7

2.9

1.3

4.9

2.0

2.2

2.5

-3.1

Multiclass SVM loss:

Given an example (x_i, y_i) where x_i is the image and where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the SVM loss has the form:

$$L_i = \sum_{j
eq y_i} \max(0, s_j - s_{y_i} + 1)$$

 $= \max(0, 5.1 - 3.2 + 1)$

 $+\max(0, -1.7 - 3.2 + 1)$

 $= \max(0, 2.9) + \max(0, -3.9)$

= 2.9 + 0

= 2.9

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_	=			<u>-</u>
ä	4			7
1			NAME OF THE OWNER OWNER OF THE OWNER	
f:			-	





cat **3.2**

car

5.1

frog -1.7

Losses: 2.9

1.3

4.9

2.0

0

2.2

2.5

-3.1

Multiclass SVM loss:

Given an example (x_i, y_i) where x_i is the image and where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the SVM loss has the form:

$$L_i = \sum_{j
eq y_i} \max(0, s_j - s_{y_i} + 1)$$

 $= \max(0, 1.3 - 4.9 + 1)$

 $+\max(0, 2.0 - 4.9 + 1)$

 $= \max(0, -2.6) + \max(0, -1.9)$

= 0 + 0

= 0







 cat
 3.2
 1.3
 2.2

 car
 5.1
 4.9
 2.5

 frog
 -1.7
 2.0
 -3.1

 Losses:
 2.9
 0
 12.9

Multiclass SVM loss:

Given an example (x_i, y_i) where x_i is the image and where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the SVM loss has the form:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$$

$$= \max(0, 2.2 - (-3.1) + 1)$$

$$+ \max(0, 2.5 - (-3.1) + 1)$$

$$= \max(0, 6.3) + \max(0, 6.6)$$

$$= 6.3 + 6.6$$

$$= 12.9$$





cat **3.2**

1.3

2.2

car

5.1

4.9

2.5

frog

-1.7

2.0

-3.1

Losses:

2.9

0

12.9

Multiclass SVM loss:

Given an example (x_i, y_i) where x_i is the image and where y_i is the (integer) label,

and using the shorthand for the scores vector: $s = f(x_i, W)$

the SVM loss has the form:

$$L_i = \sum_{j
eq y_i} \max(0, s_j - s_{y_i} + 1)$$

Loss over full dataset is average:

$$L = rac{1}{N} \sum_{i=1}^{N} L_i$$

$$L = (2.9 + 0 + 12.9)/3$$

= **5.27**

Objective Function

$$L=rac{1}{N}\sum_{i=1}^{N}\sum_{j
eq y_i}\max(0,f(x_i;W)_j-f(x_i;W)_{y_i}+1)+\lambda R(W)$$

In common use:

L2 regularization
$$R(W) = \sum_{k} \sum_{l} W_{k,l}^2$$

L1 regularization $R(W) = \sum_{k} \sum_{l} |W_{k,l}|$

Elastic net (L1 + L2) $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$

Objective Function (SVM_LOSS) Minimization

```
close all; clear all; clc;
%Loading Data
load Airplanes
load Leopards
load Motorbikes
%Feature size = N
[ddd,N]=size(C1);
f=0(X)SVMLOSS(X,C1,C2,C3);
options = optimoptions('fmincon','Display','iter','Algorithm','sqp');
A=[];b=[];Aeq=[];beq=[];lb=[];ub=[];nonlcon = [];
W=2*rand(3*(N+1),1)-1;
[W,fv] = fmincon(f,W,A,b,Aeq,beq,lb,ub,nonlcon,options)
save('W.mat','W')
```

Optimization Results

