

Un approccio efficiente basato sul machine learning per il rilevamento di micro-espressioni facciali

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Automatic detection of the emotional state of a subject Sentiment analysis

Real weight of communication

verbal: 7%

paraverbal: 38%

non verbal: 55%

Albert Mehrabian, Nonverbal Communication, Taylor & Francis Inc, 2007 *(from 1972)*

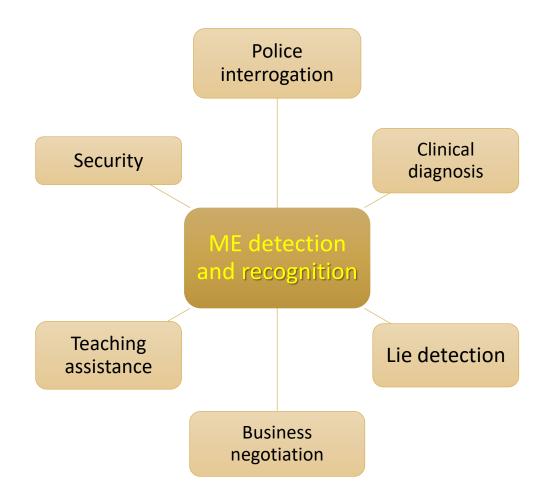


THE TIMID PUPIL" LA MESANGERE, Paris (about 1800



SAPIENZA Problem: some applications

Automatic detection of the emotional state of a subject in a video sequence



SAPIENZA Problem: Investment 2020

By the way: Automatic 'control' of customers emotional state:

Some interested enterprises: GE Cisco IBM AutoDesk Qualcomm

Investment in 2020 about 20 billions of dollars

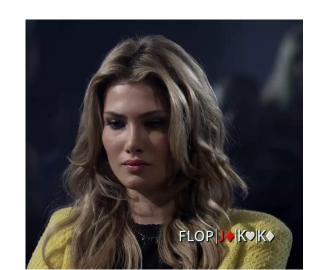
Other examples:Apple acquired EmotientNielsen acquired Innerscope

Unilever P&G Mars Honda Kellogg Coca Cola





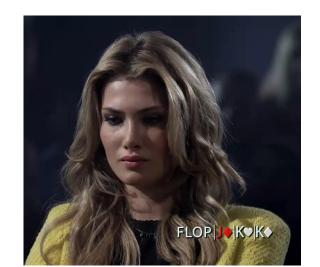
ME definition:"very brief, subtle, and involuntary facial expressions which
normally occur when a person either deliberately or
unconsciously conceals his or her genuine emotions"





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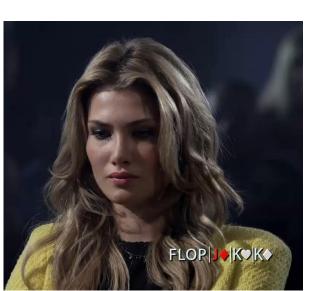
ME duration: MEs are characterized by a very short duration ranging from 1/25 to 1/5 of a second (maximum duration: 1/2 second)







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ME pros and cons

spontaneous and very *informative*: minute muscle movements reflect the true emotions of a person

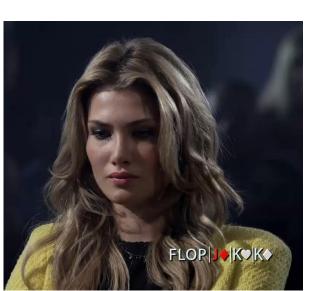
hard to detect: due to the short duration and low intensity, they are very difficult to perceive and interpret correctly





from 40 ms to 200 ms

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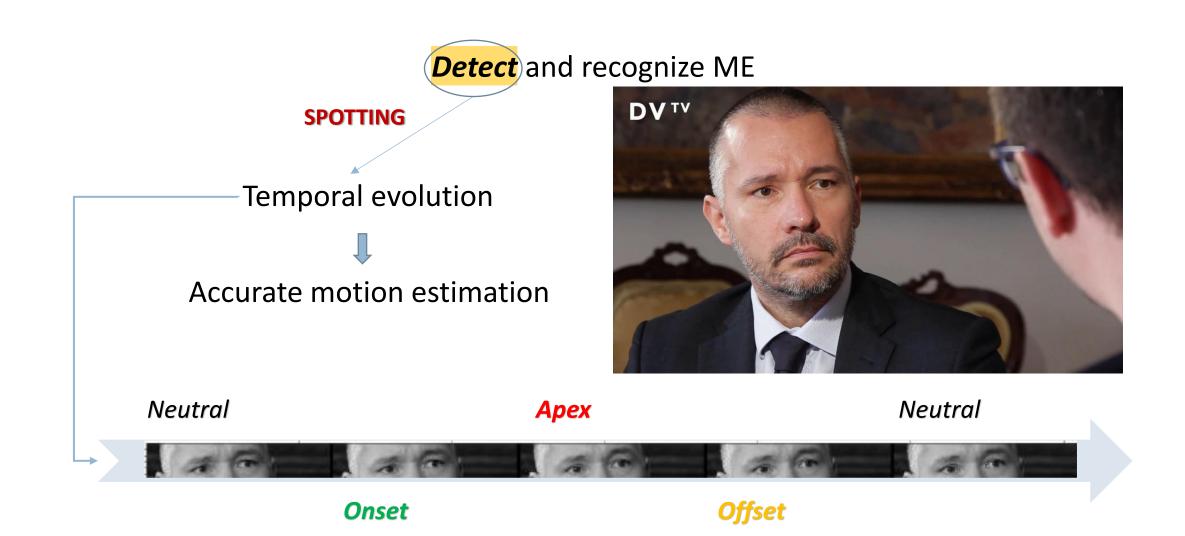
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Preattentive Processing

200 ms

hard to detect: due to the short duration and low intensity, they are very difficult to perceive and interpret correctly









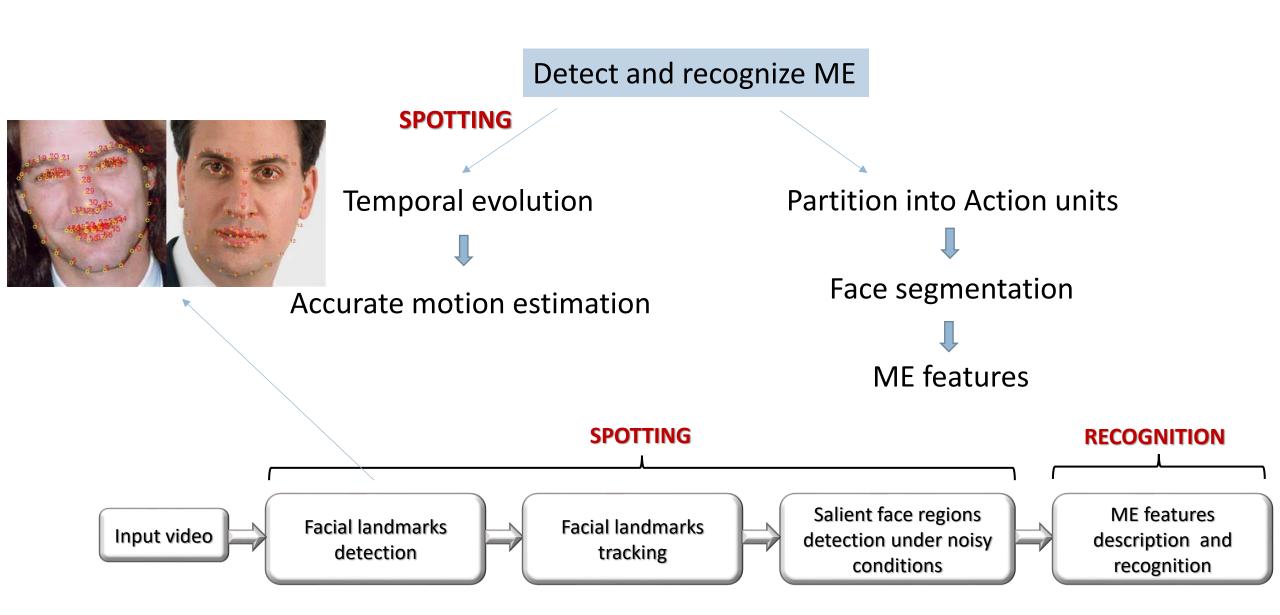
Paul Ekman

			Detect a	and <mark>rec</mark>	ognize l	ME	
	AU 9	AU 10	AU 11	AU 12	AU 13	AU 14	
	The second	1	that .	10	-	1	Partition into Action Units
	Nose Wrinkler	Upper Lip Raiser	Nasolabial Deepener	Lip Corner Puller	Cheek Puffer	Dimpler	
	AU 15	AU 16	AU 17	AU 18	AU 20	AU 22	
	12		30		-	0	Face segmentation
	Lip Corner	Lower Lip	Chin	Lip	Lip	Lip	
	Depressor	Depressor	Raiser	Puckerer	Stretcher	Funneler	
	AU 23	AU 24	*AU 25	*AU 26	*AU 27	AU 28	
	-	3	-	N=/	se,		ME features
	Lip	Lip	Lips	Jaw	Mouth	Lip	
	Tightener	Pressor	Part	Drop	Stretch	Suck	

44 action units: each AU describes facial deformation due to each facial muscle movement

AUs involve contraction or relaxation of facial muscles and miscellaneous actions





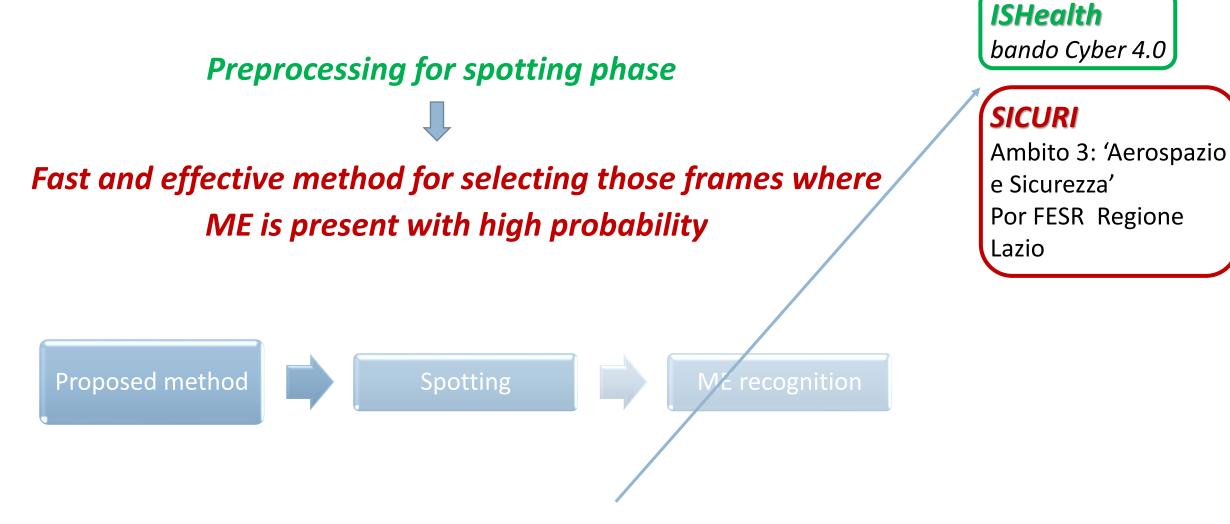


Preprocessing for spotting phase

Fast and effective method for selecting those frames where ME is present with high probability







Aim: to make faster the detection process



- MEs as temporal transients
- ME as visual fingerprint

- → Visual discontinuties
- Perceptual Expression
 Signature (PES)





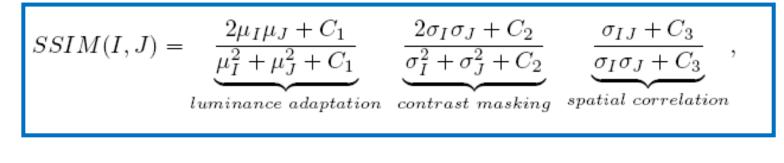
✓ simple IQA metric: **SSIM** (Structural **SIM**ilarity index)

✓ global feature: temporal behaviour of the asymmetry of SSIM distribution



• simple IQA metric: SSIM





-1 ≤ *SSIM(I,J)* ≤ 1

The closer SSIM to 1, the higher the similarity between I and J

Remark: SSIM doesn't satisfy *triangle inequality* or *non-negativity*: **not a distance**. Under certain conditions, SSIM can be a normalized root MSE measure (distance), the square of such a function is not convex, but is *locally convex* and *quasiconvex*.

Wang, Zhou; Bovik, A.C.; Sheikh, H.R.; Simoncelli, E.P. (2004-04-01). "Image quality assessment: from error visibility to structural similarity". *IEEE Transactions on Image Processing*. **13** (4): 600–612

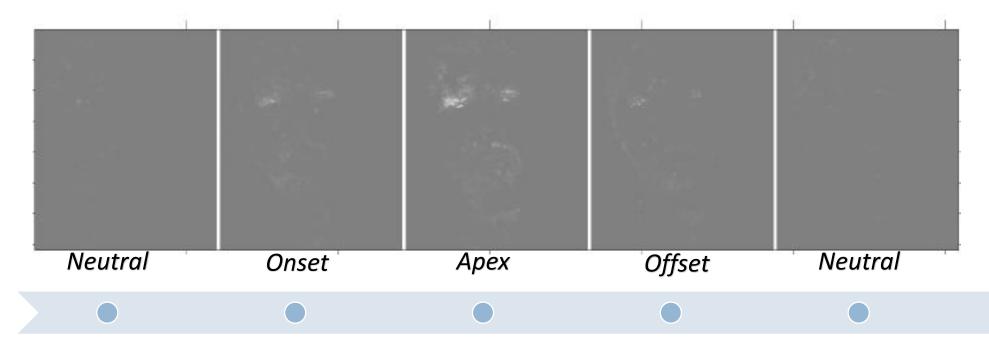




• simple IQA metric: SSIM

the larger S the higher the visual dissimilarity between two consecutive frames

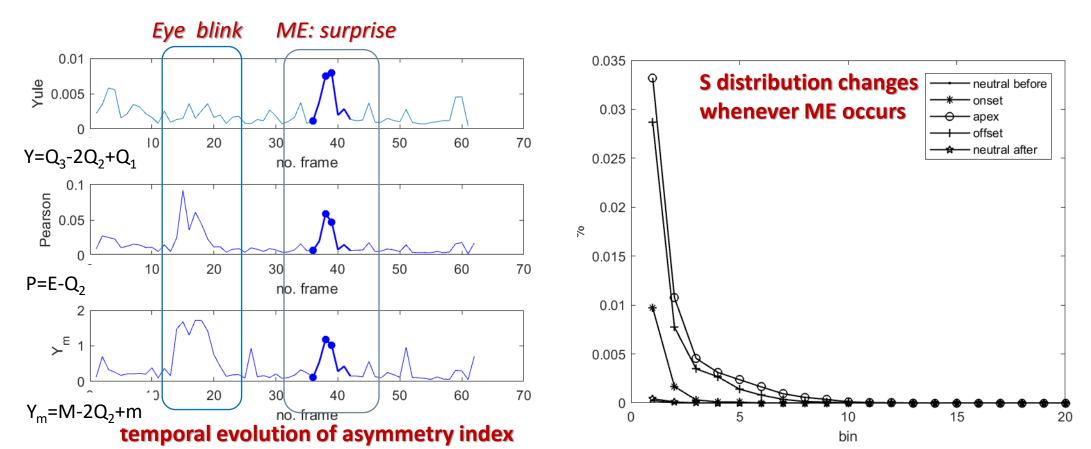
 $S(I,J) = 1 - SSIM(I,J) = 1 - \frac{2\mu_I\mu_J + C_1}{\mu_I^2 + \mu_J^2 + C_1} \frac{2\sigma_{IJ} + C_2}{\sigma_I^2 + \sigma_J^2 + C_2}$



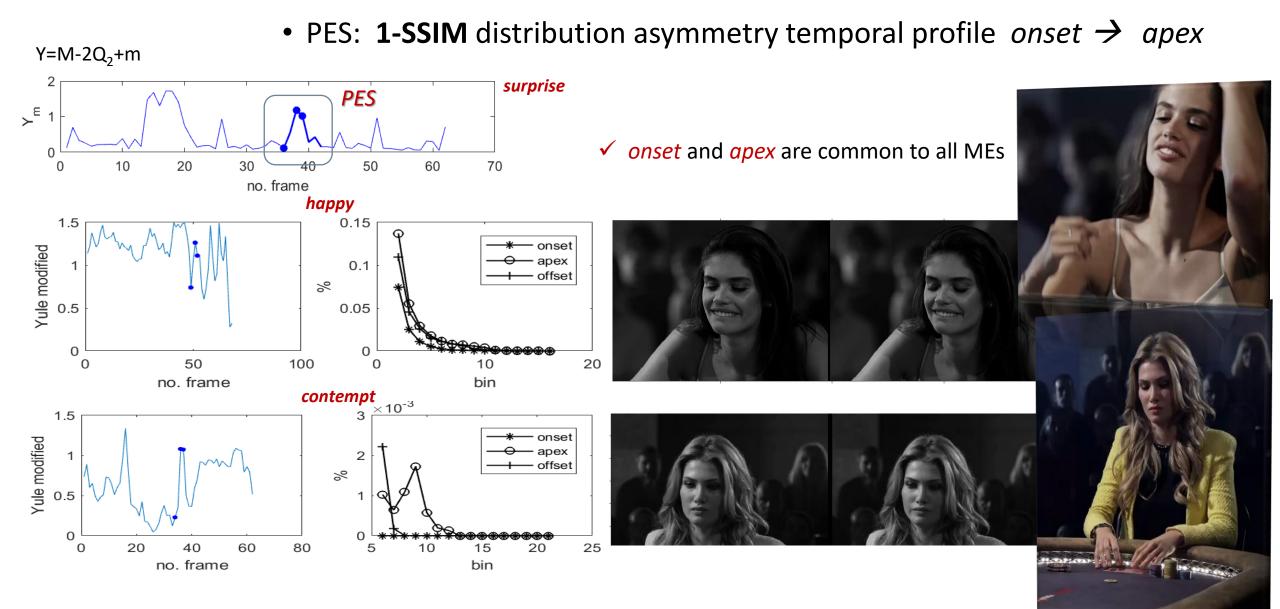




Global feature: *asymmetry* of *S=1-SSIM* distribution in a global ROI (the face)







SAPIENZA Machine Learning: Support Vector Machine

SVM solves the binary classification problem as a supervised learning task

Starting from a *training set*:

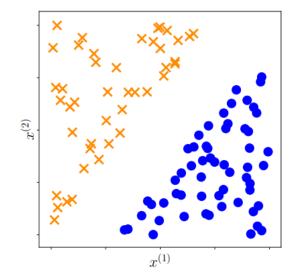
Gender ID	Degree	Latitude	Longitude	Age	Annual Salary
		(in degrees)	(in degrees)		(in thousands)
-1	2	51.5073	0.1290	36	89.563
-1	3	51.5074	0.1275	47	123.543
+1	1	51.5071	0.1278	26	23.989
-1	1	51.5075	0.1281	68	138.769
+1	2	51.5074	0.1278	33	113.888

where there is a set of examples $\mathbf{x}_n \in R^D$ with their corresponding (binary) labels $y_n \in \{+1, -1\}$

The parameters of the model, giving the smallest classification error, must be estimated

Why SVM: it allows for a simple geometric way to think about supervised machine learning

Example on 2D data:



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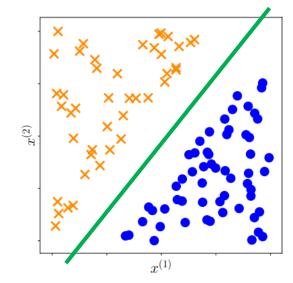
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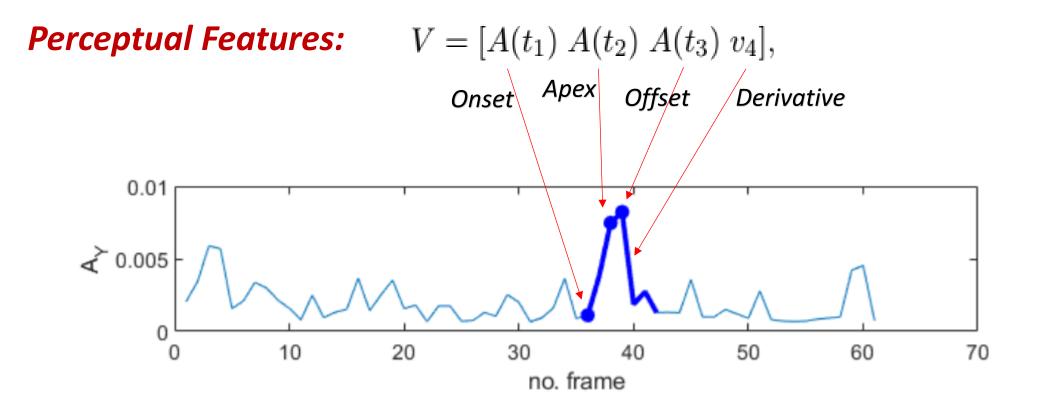
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SAPIENZA UNVERSITA DI ROMA MAChine Learning: Support Vector Machine



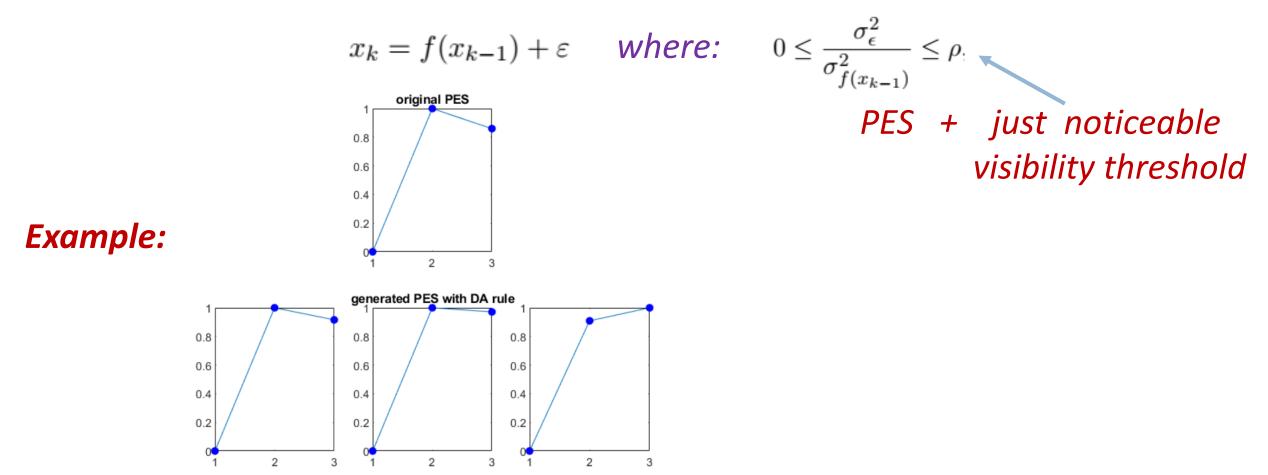
where: $v_4 \in \{-1, +1\}$





Problem: lack of data (necessary for SVM)

Solution: Data Augmentation (adding a subtle visual noise)

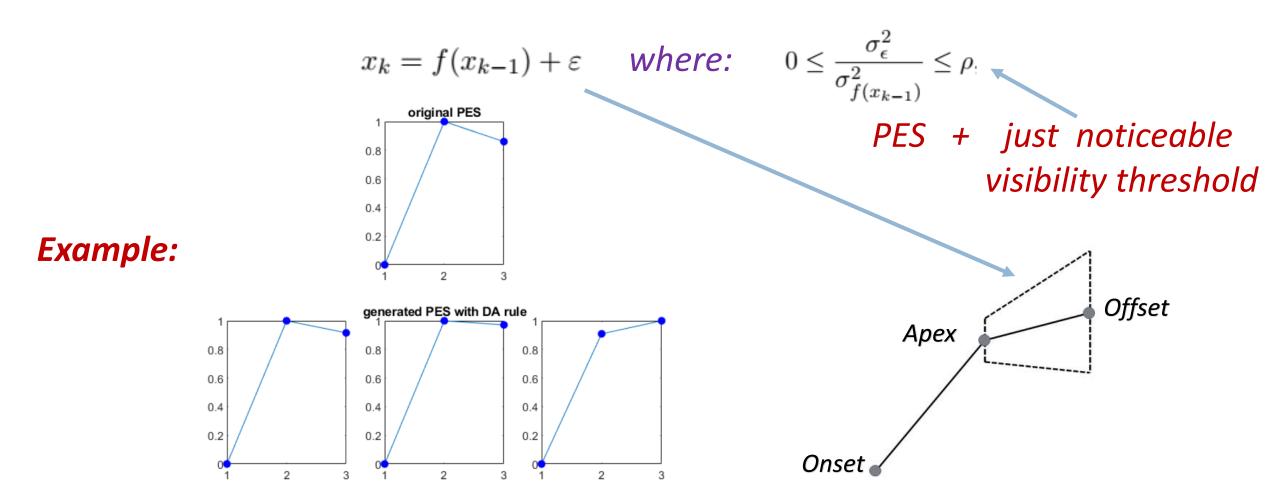


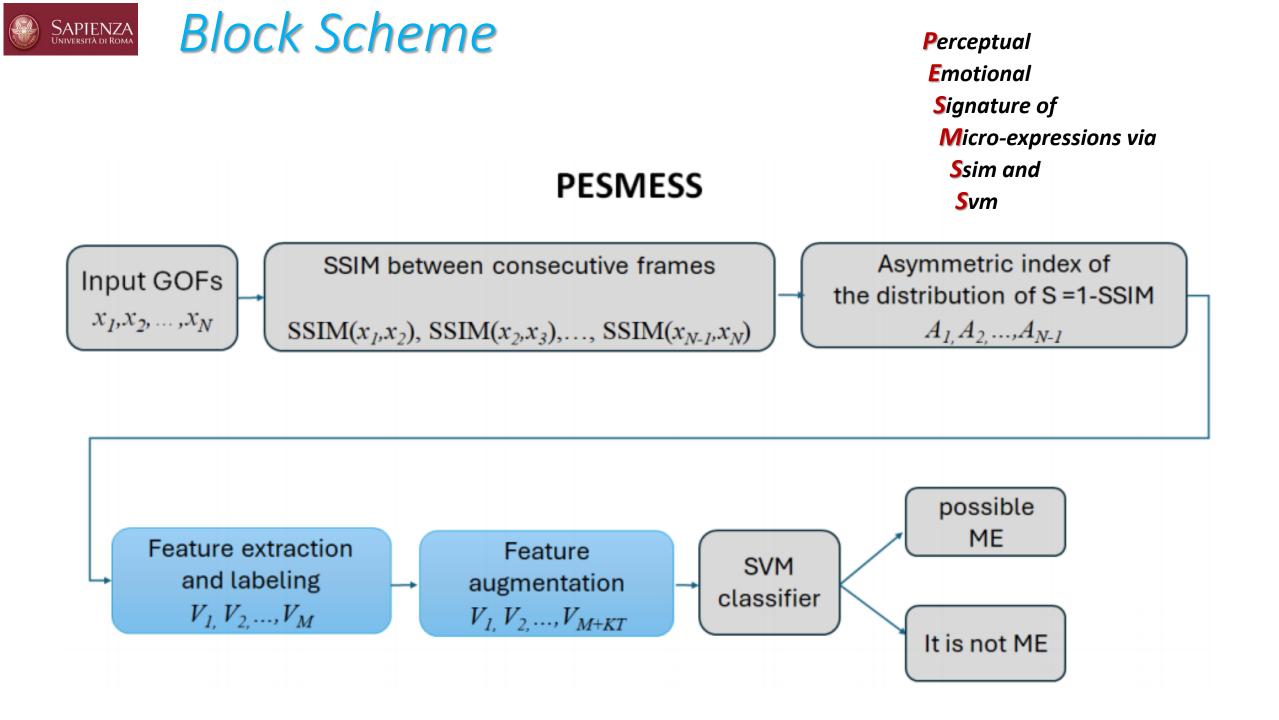




Problem: lack of data (necessary for SVM)

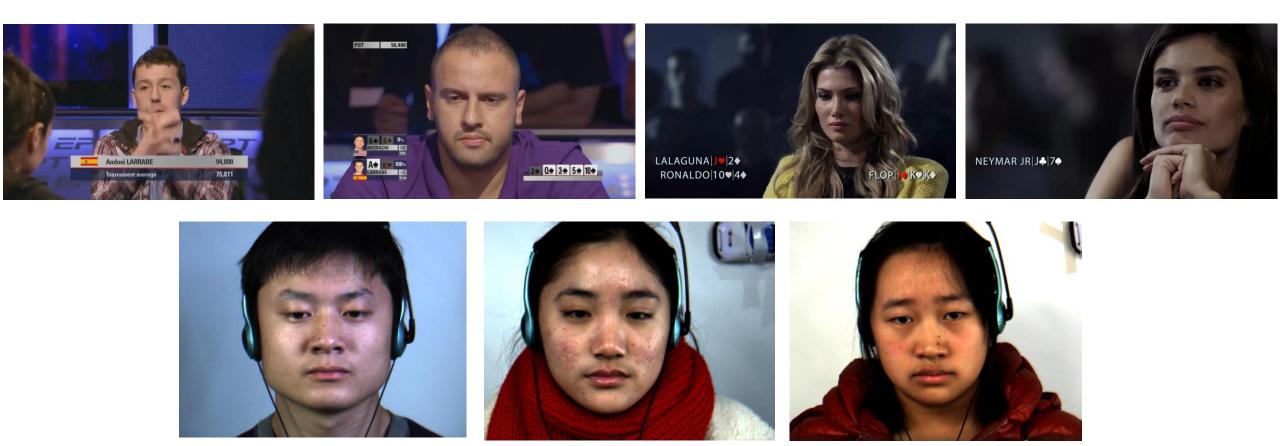
Solution: Data Augmentation (adding a subtle visual noise)







Adopted Databases: MEVIEW: "in-the-wild" situations, with realistic poker game videos, 31 videos, 3s **CASME II:** (247 videos, 200 fps, MEs (less than .2 secs)

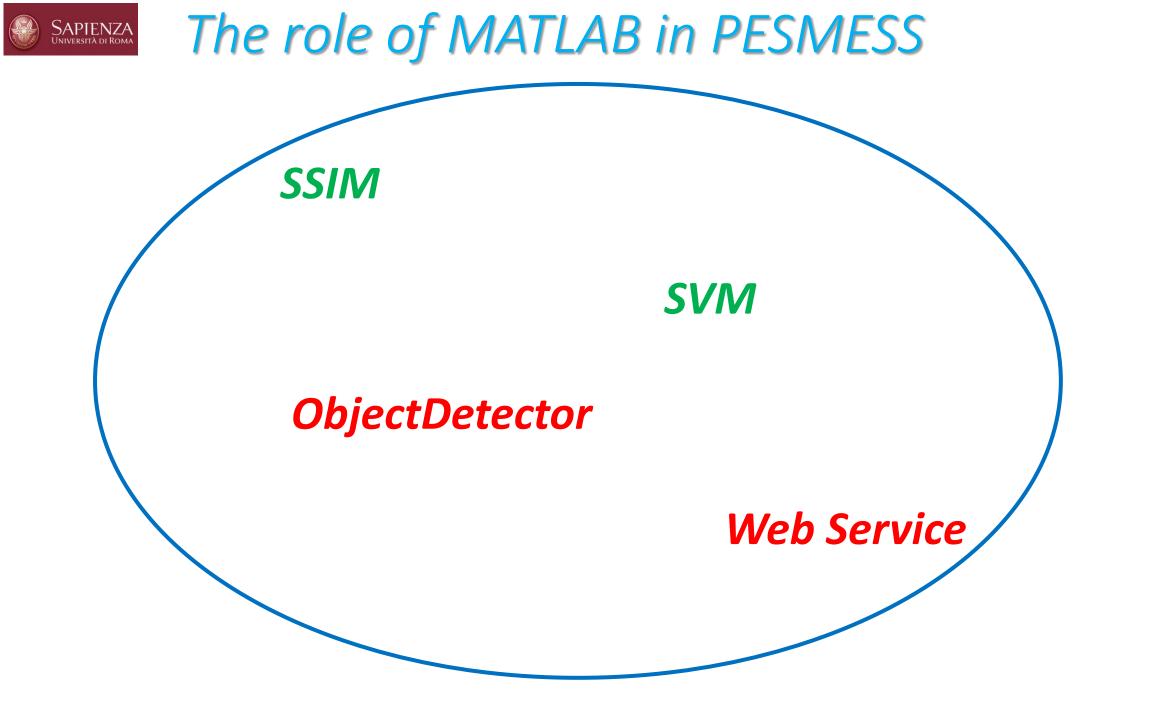


SAPIENZA DOES PESMESS work?

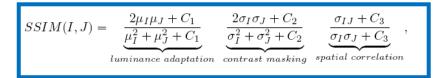
Note: few false alarms , 102 elements (positive and negative training examples), $\rho = 0.33\%$

Sequence: 15.1								
PES no. 1	Location	3	Description	looks up				
PES no. 2	Location	23	Description	open eyes				
PES no. 3	Location	38	Description	ME (surprise)				
Sequence: 14.3								
PES no. 1	Location	5	Description	imperceptible smile				
PES no. 2	Location	19	Description	ME (joy)				
Sequence: 1.1								
PES no. 1	Location	12	Description	zoom/stabilization				
PES no. 2	Location	35	Description	zoom/stabilization				
PES no. 3	Location	48	Description	ME begin				
PES no. 4	Location	54	Description	ME reinforcement				
PES no. 5	Location	64	Description	ME end				
PES no. 6	Location	73	Description	mouth micro movement				
Sequence: 2.1								
PES no. 1	Location	29	Description	look down				
PES no. 2	Location	81	Description	frozen eyes				
PES no. 3	Location	99	Description	ME				
Sequence: 3.1								
PES no. 1	Location	27	Description	looks up				
PES no. 2	Location	37	Description	frozen eyes				
PES no. 3	Location	70	Description	mouth movement				
PES no. 4	Location	78	Description	ME				
Sequence: 6.1								
PES no. 1	Location	3	Description	keep looking down				
PES no. 2	Location	15	Description	ME				
PES no. 3	Location	34	Description	eyes movement				
PES no. 4	Location	47	Description	eyes and eyebrows				

			-				
Sequence: 7.9							
PES no. 1	Location	13	Description	mouth movement			
PES no. 2	Location	27	Description	tongue movement			
PES no. 3	Location	31	Description	tongue movement			
PES no. 4	Location	46	Description	head movement			
PES no. 5	Location	50	Description	head (FA)			
PES no. 6	Location	60	Description	eyes movement			
PES no. 7	Location	65	Description	tongue movement			
PES no. 7	Location	65	Description	ME			
		S	equence: 8.1				
PES no. 1	Location	13	Description	ME			
PES no. 2	Location	22	Description	mouth (ME end)			
PES no. 3	Location	32	Description	head movement			
PES no. 4	Location	42	Description	eyes movement			
PES no. 4	Location	46	Description	head movement			
PES no. 5	Location	49	Description	head movement			
PES no. 6	Location	56	Description	head movement			
Sequence: 8.2							
PES no. 1	Location	19	Description	ME			
PES no. 2	Location	37	Description	head movement			
PES no. 3	Location	43	Description	head and eyes movement			









 $2\sigma_I\sigma_J + C_2$ $2\mu_I\mu_J + C_1$ $\sigma_{IJ} + C_3$ SSIM(I, J) = $\sigma_T^2 + \sigma_T^2 + C$ $\sigma_I \sigma_J + C_3$ spatial correlation luminance adaptation contrast masking

[Ssimval,Sssimmap] = ssim(A,ref)

SAPIENZA UNIVERSITÀ DI ROMA The role of MATLAB in PESMESS: SSIM

 $\sigma_{IJ} + C_3$

 $\underbrace{\sigma_I \sigma_J + C_3}_{spatial \ correlation}$

 $2\sigma_I\sigma_J + C_2$

contrast masking



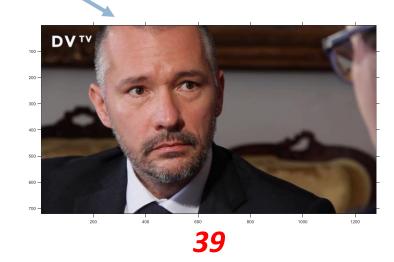
[Ssimval,Sssimmap] = ssim(A,ref)

 $2\mu_I\mu_J + C_1$

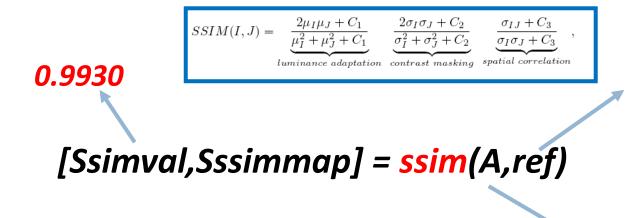
luminance adaptation

SSIM(I, J) =

38



SAPIENZA UNIVERSITÀ DI ROMA The role of MATLAB in PESMESS: SSIM

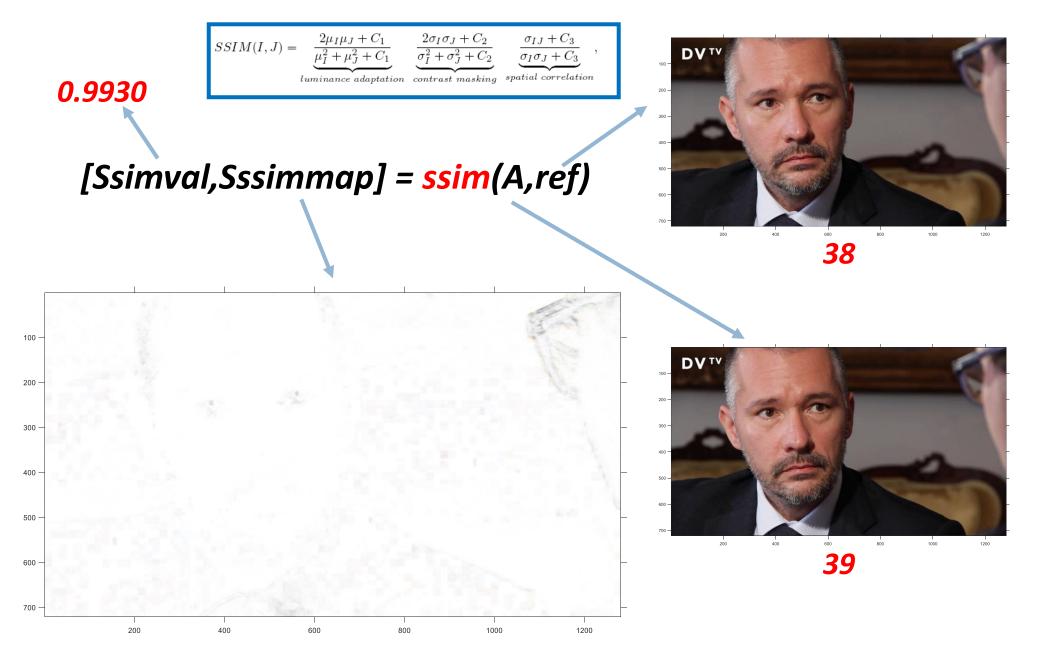




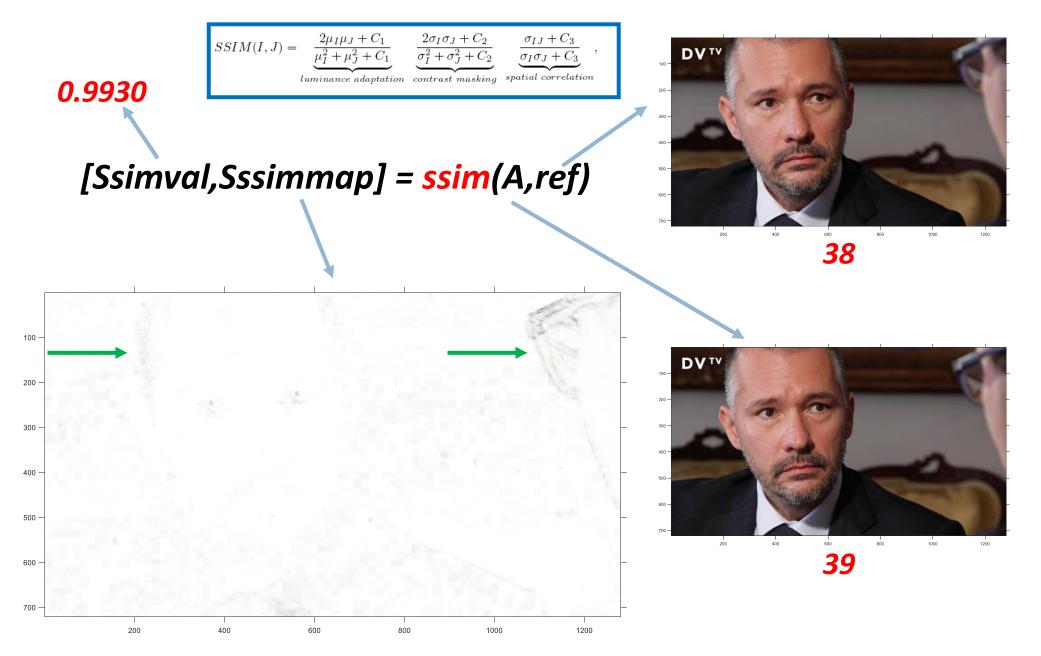
38



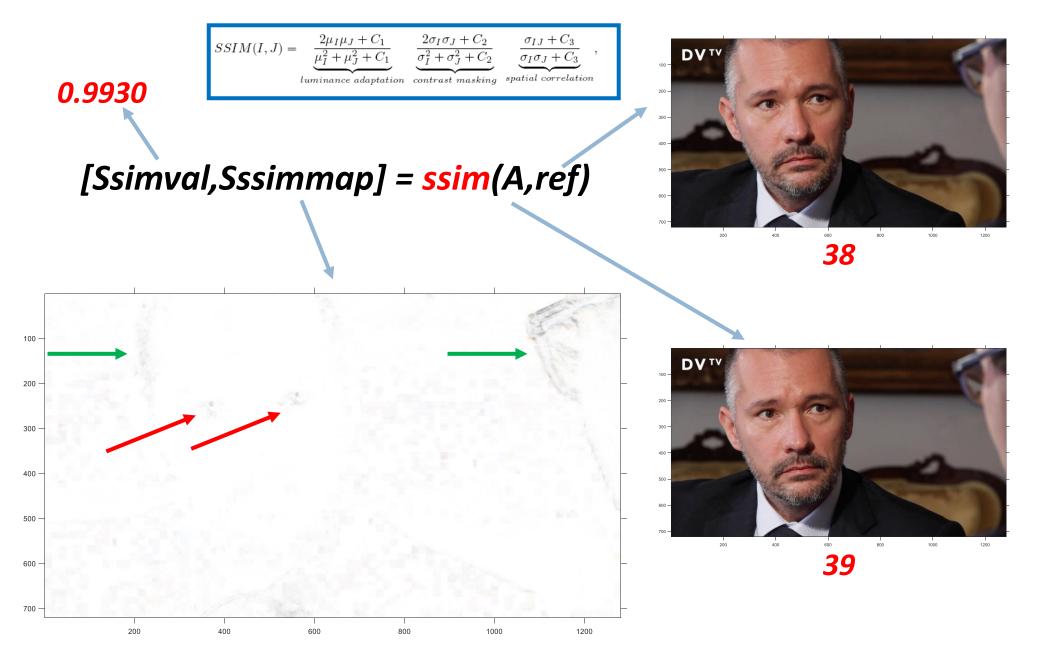
SAPIENZA UNIVERSITÀ DI ROMA THE role of MATLAB in PESMESS: SSIM



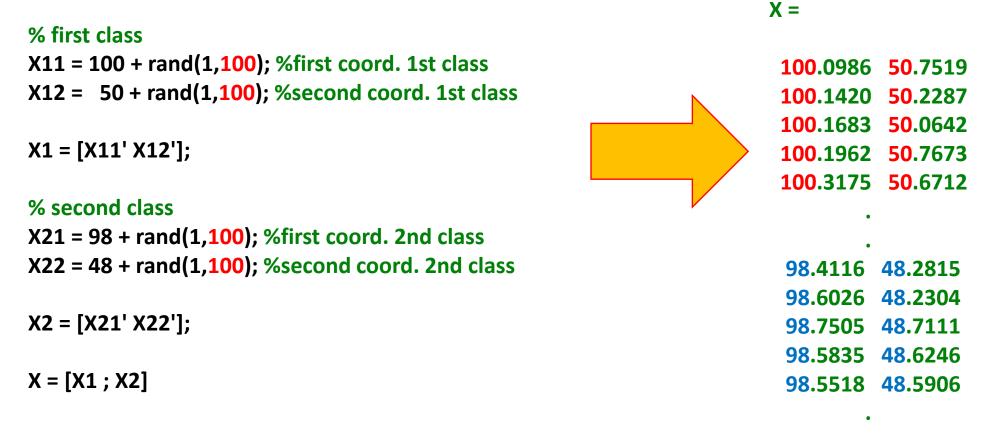
SAPIENZA UNIVERSITÀ DI ROMA The role of MATLAB in PESMESS: SSIM



SAPIENZA UNIVERSITÀ DI ROMA The role of MATLAB in PESMESS: SSIM



Let's generate synthetic data (training set, noisy data around 2 centers of mass with coordinates (100,50) and (98,48):



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		X =	
% first class			
X11 = 100 + rand(1,100); %first coord. 1st class		100 .0986 50 .7519	
X12 = 50 + rand(1,100); %second coord. 1st class		100.1420 50.2287	
		100.1683 50.0642	Y =
X1 = [X11' X12'];		100.1962 50.7673	200×1 cell array
		100.3175 50.6712	
% second class			{'c'}
X21 = 98 + rand(1,100); %first coord. 2nd class			{'c'}
X22 = 48 + rand(1,100); %second coord. 2nd class		98.4116 48.2815	{'c'}
		98.6026 48.2304	[ט
X2 = [X21' X22'];		98.7505 48.7111	•
		98.5835 48.6246	{'g'}
X = [X1 ; X2]	Y = <mark>cell(</mark> 200,1);	98.5518 48.5906	{'g'}
			{'g'}
	for i=1:100, Y{i} = 'c', end		
	for i=101:200, Y{i} = 'g', end		

Let's generate synthetic data (training set, noisy data around 2 centers of mass with coordinates (100,50) and (98,48):

Y =

{'c'}

{'c'}

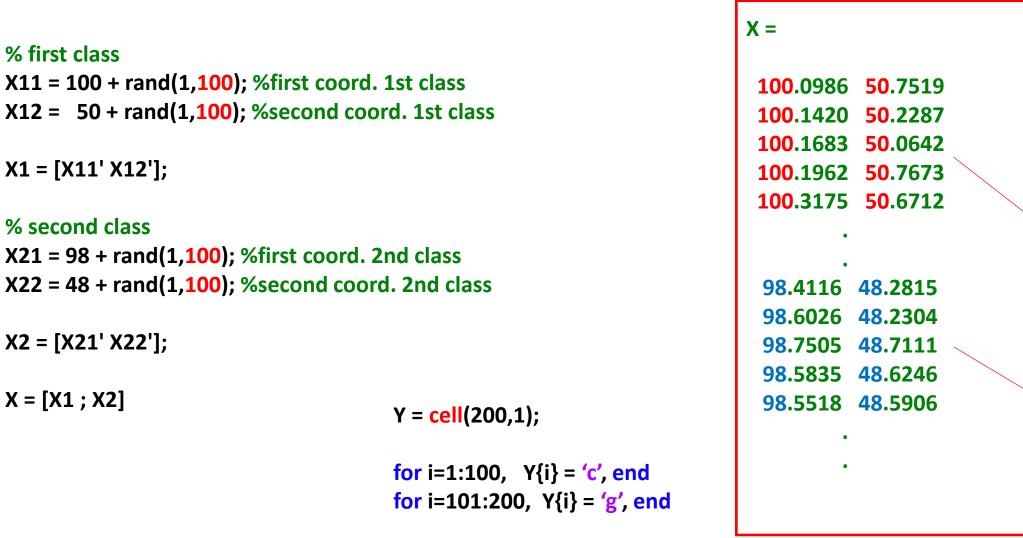
{'c'}

{'g'}

{'g'}

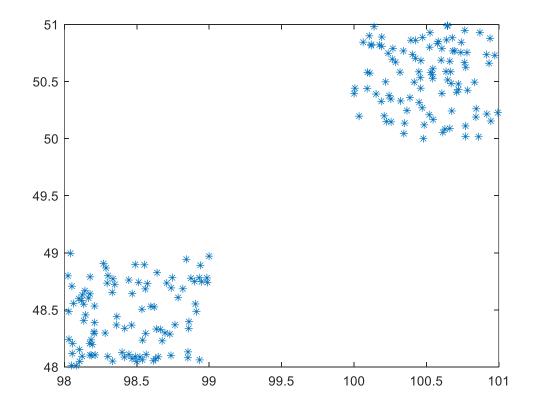
{'g'}

200×1 cell array



SAPIENZA The role of MATLAB in PESMESS: SVM

Let's generate synthetic data (training set, noisy data around 2 centers of mass with coordinates (100,50) and (98,48):



Learning model:

SVMModel = fitcsvm(X,Y,'KernelFunction','rbf',... % per classificazione binaria 'Standardize',true,'ClassNames',{'c','g'});

SVMModel =

ClassificationSVM **ResponseName: 'Y'** CategoricalPredictors: [] ClassNames: {'c' 'g'} ScoreTransform: 'none' NumObservations: 200 Alpha: [8×1 double] Bias: -0.0074 KernelParameters: [1×1 struct] Mu: [99.5048 49.4672] Sigma: [1.0565 1.0218] BoxConstraints: [200×1 double] **ConvergenceInfo:** [1×1 struct] IsSupportVector: [200×1 logical] Solver: 'SMO'

The role of MATLAB in PESMESS: SVM SAPIENZA UNIVERSITÀ DI ROMA

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SAPIENZA UNIVERSITA DI ROMA THE ROLE OF MATLAB IN PESMESS: SVM

Prediction data (test set) generation :

% P R E D I C T %new samples Xn11 = 100 + rand(1,10); %first coord. 1st class Xn12 = 50 + rand(1,10); %first coord. 1st class

Xn1 = [Xn11' Xn12'];

%second class Xn21 = 98 + rand(1,10); %first coord. 2nd class Xn22 = 48 + rand(1,10); %first coord. 2nd class

Xn2 = [Xn21' Xn22'];

%all in one

Xn = [Xn1 ; Xn2];

Prediction phase:

.

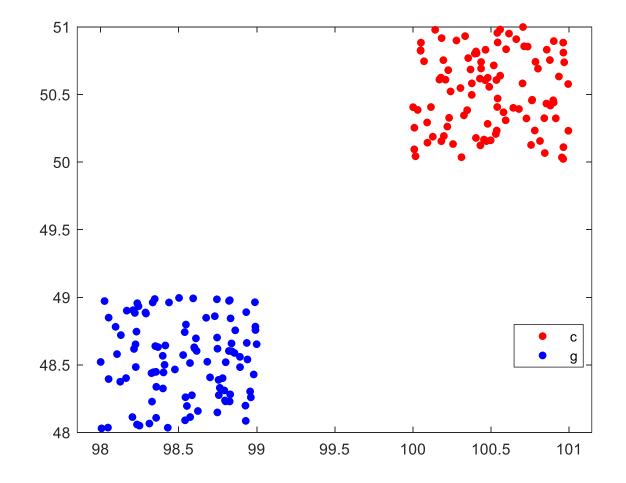
.

```
d = 0.02;
[x1Grid,x2Grid] = meshgrid(min(Xn(:,1)):d:max(Xn(:,1)),min(Xn(:,2)):d:max(Xn(:,2)));
xGrid = [x1Grid x2Grid(:)];
[~,scores] = predict(SVMModel,xGrid);
%[label,score] = predict(SVMModel,Xn); % altro predict sui dati test
label =
                  Prediction phase:
 20×1 cell
                                                          % likelihood that a label comes from a particular class
                  score =
array
                     1.1398 -1.1398
  {'c'}
                     1.1737 -1.1737
  {'c'}
                     1.0761 -1.0761
  {'c'}
                     1.0906 -1.0906
  {'c'}
                     1.0687 -1.0687
  {'c'}
```

SAPIENZA The role of MATLAB in PESMESS: SVM

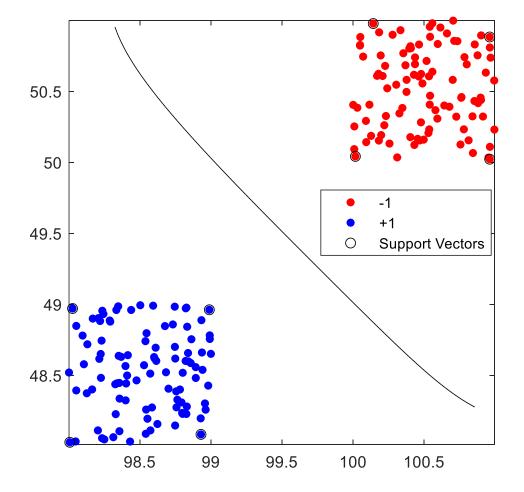
Prediction phase:

Initial data



Prediction phase:

with hyperplane and support vectors

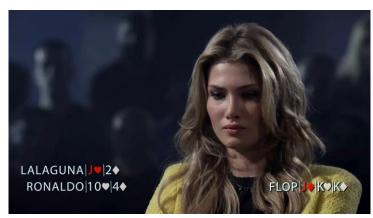




The role of MATLAB in PESMESS: vision.CascadeObjectDetector

Problem: too many faces

Solution: The cascade object detector uses the Viola-Jones algorithm (2021) to detect people's faces, noses, eyes, mouth, or upper body



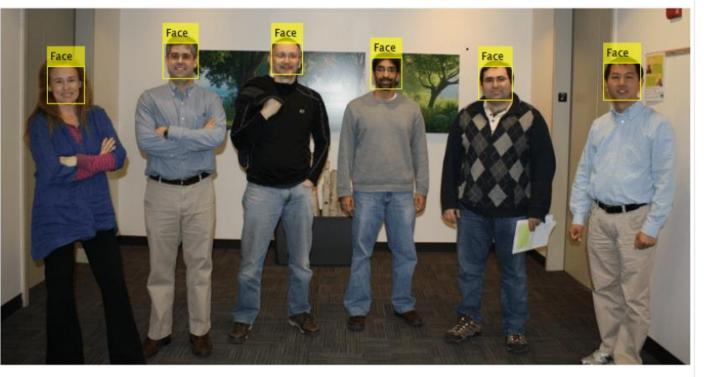






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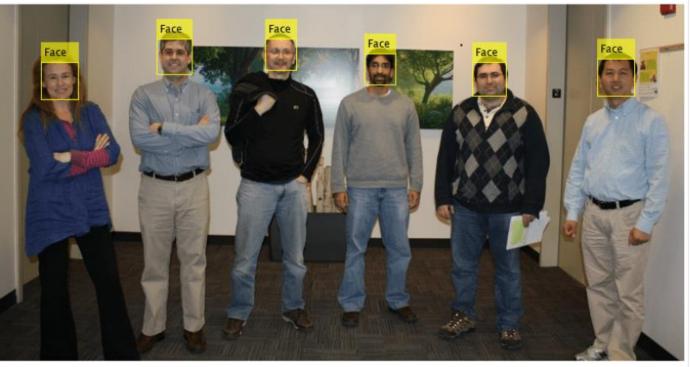


	 Detect Faces in an Image Using the Frontal Face Classification Model 	
	Create a face detector object.	
	<pre>faceDetector = vision.CascadeObjectDetector;</pre>	
Read the input image.		
	<pre>I = imread('visionteam.jpg');</pre>	
	Detect faces.	
	<pre>bboxes = faceDetector(I);</pre>	
	Annotate detected faces.	
	<pre>IFaces = insertObjectAnnotation(I, 'rectangle', bboxes, 'Face'); figure imshow(IFaces) title('Detected faces');</pre>	



The role of MATLAB in PESMESS: vision.CascadeObjectDetector

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The role of MATLAB in PESMESS: Web Service





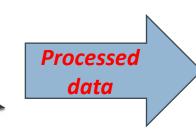


SAPIENZA UNVERSITA DU ROMA The role of MATLAB in PESMESS: Web Service







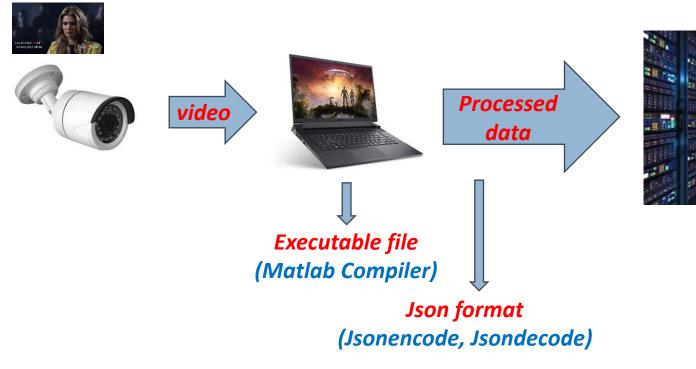






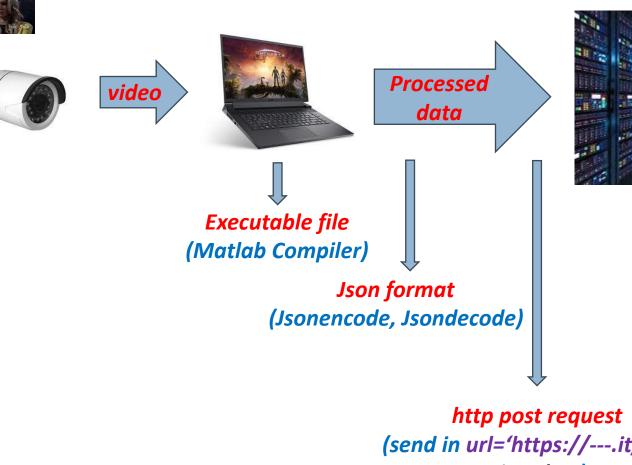
Executable file (Matlab Compiler)

SAPIENZA UNVERSITÀ DI ROMA The role of MATLAB in PESMESS: Web Service





The role of MATLAB in PESMESS: Web Service SAPIENZA UNIVERSITÀ DI ROMA

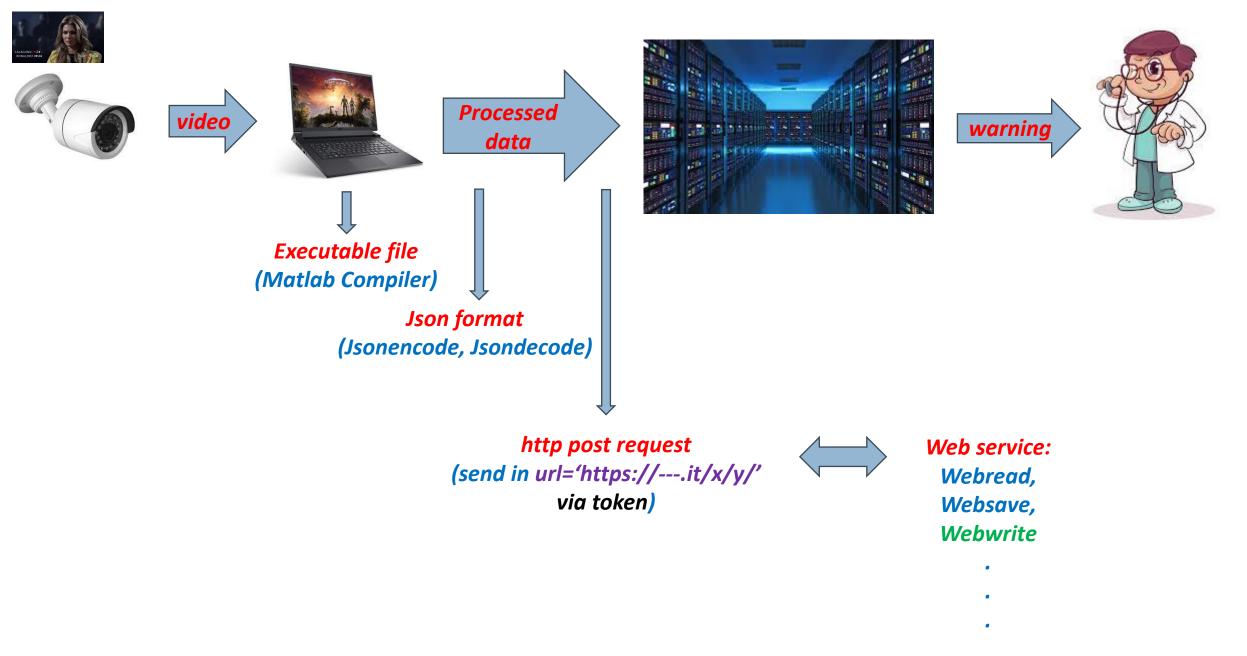






(send in url='https://---.it/x/y/' via token)

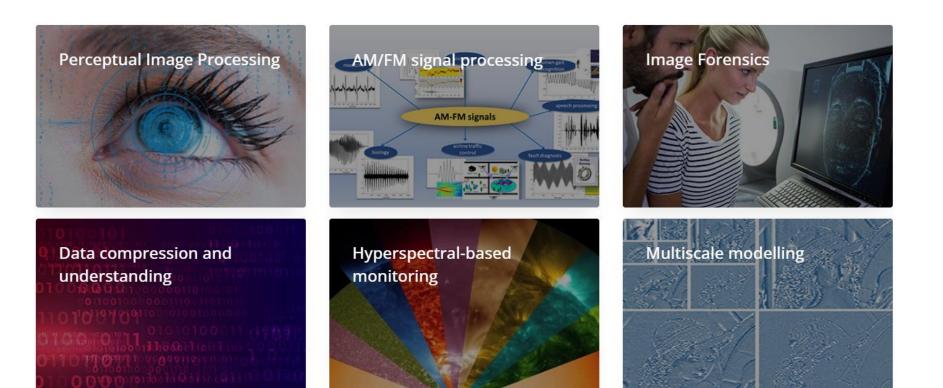
SAPIENZA UNVERSITÀ DI ROMA The role of MATLAB in PESMESS: Web Service











Vittoria Bruni





THANKS & LOT FOR YOUR & TTENTION