





# M2CAL WORKFLOW CHALLENGE 2016 Fine tuning CNN with HMM smoothing

21th October 2016

Rémi Cadène, Thomas Robert, Nicolas Thome, Matthieu Cord

University Pierre and Marie Curie - LIP6 - MLIA

### M2CAI Workflow Dataset

Context





Videos resolution is  $1920 \times 1080$ , shot at 25 frames per second at the IRCAD research center in Strasbourg, France.

- 27 training videos ranging from 15mn to 1hour
- 15 test videos

### M2CAl Workflow Dataset

Context



#### 1 of 8 classes for each frames:

- TrocarPlacement
- Preparation
- CalotTriangleDissection
- ClippingCutting
- GallbladderDissection
- GallbladderPackaging
- CleaningCoagulation
- GallbladderRetraction

### M2CAI Workflow Goal and Measure



Online prediction :  $P(y|x_i, x_{i-1}, x_{i-2}, ...)$ 

 $x_i := \text{frame } i, \text{ and } y := \text{classes}$ 

Useful to:

Context

- monitor surgeons
- trigger automatic actions

Measures: - Jaccard similarity coefficient:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

- Accuracy top1 : nb frames well classified / nb total frames

### Two fold approach



# 1. Model to classify frames as images

- Extract features from pre-trained CNN
- CNN From Scratch
- Fine tuning pre-trained CNN

# 2. Smoothing predictions of our frames classifier

- 1 Averaging predictions over 15 frames
- 2 Hidden Markov Model as a "denoizer" (HMM)

# 1. Creating validation set and extracting images



Spliting randomly the full training set of 27 videos

■ training set : 22 videos

■ validation set : 5 videos {2, 9, 10, 13, 27}

Extracting one frame every 25 frames (1 frame per second)

■ training set : 59,493 images

■ validation set: 8,062 images

■ testing set : 28,732 images



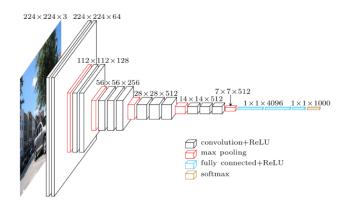
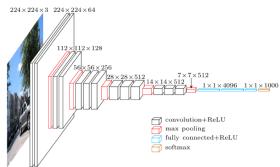


Figure 1 - Vgg16 [simonyan2014very], top2 ILSVRC2014



#### Pre-trained CNN as Features Extractor

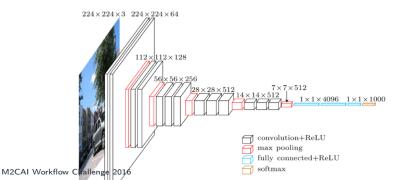
- Remove last layer, Add new layer output size 8, Train with SGD fixing the pre-trained layers
- Extract features somewhere, Train a SVM





### Training a CNN From Scratch

- Design specific CNN architecture
- Reinitialized architecture designed for large datasets with strong regularization

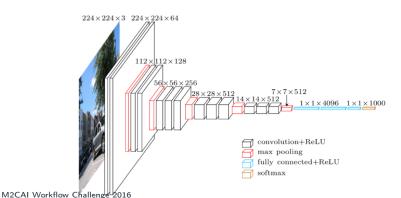


# UPMC

### Fine tuning a pre-trained CNN

■ SGD : Ir, Ird, ftfactor

Adam : Ir, Ird





Model	Input	Param.	Depth	Implem.	Time (ms)
Vgg16	224	138M	16	GPU	
InceptionV3	399	24M	42	GPU	0
ResNet-200	224		200	GPU	
InceptionV3	399	24M	42	CPU	0

Table 1 – Forward+Backward with batches of 30 images.

### 3. Smoothing the predictions



Averaging the predictions across the last 15 frames (15 seconds)

Hidden Markov Model on the predictions 3 kind of parameters the initial state probabilities the matrix of probabilities of transition between states the emissions of observations

# 3. Smoothing the predictions



HMM has

Training: counting

Offline testing: Viterbi algorithm to obtain the most likely

sequence of states

Online testing: to predict  $x_t$  we apply Viterbi on the sequence

 $V_1, \ldots, V_t$ 

# Comparison of frames classifiers

Classification Model	Accuracy (%)	
InceptionV3 Extraction	60.53	
InceptionV3 From Scratch	69.13	
InceptionV3 Weldon	78.18	
InceptionV3 Fine-tuned	79.06	
ResNet200 Fine-tuned	79.24	

Table 2 – Accuracy on the validation set.

# Comparison of temporal smoothing methods

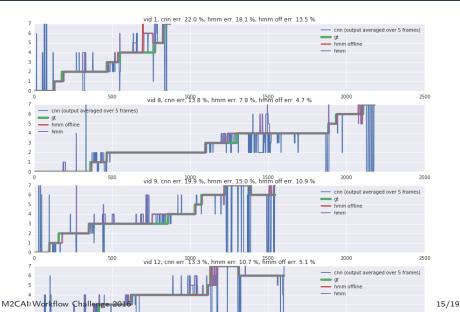


Temporal Method	Accuracy (%)	Jaccard
Avg Smoothing	$85.97 \pm 3.75$	$74.67 \pm 7.87$
HMM Online	$88.90 \pm 3.55$	$81.60 \pm 10.49$
HMM Offline	$93.47 \pm 3.59$	$87.59 \pm 6.97$

Table 3 – Accuracy Top1 and Jaccard score on the validation set. The variance is computed over all classes.

### Visualization





### Conclusion

# 18 AL SORBONNE UNIVERSIT

### Conclusion

- Deep Learning efficient
- Fine Tuning most accurate approach
- HMM is usefull to smooth the predictions

### Future work

- train on 100%
- ensembling

Code available : github.com/Cadene/torchnet-m2caiworkflow

