M2CAI WORKFLOW CHALLENGE 2016

Fine tuning CNN with temporal smoothing and HMM for video frames classification

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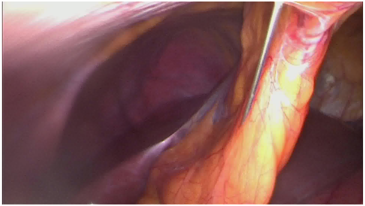
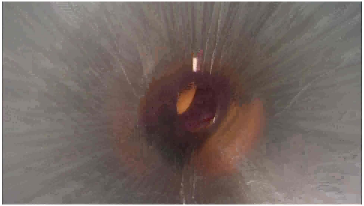
M2CAI Workflow Dataset





Endoscopic videos, resolution of 1920 x 1080, shot at 25 frames per second at the IRCAD research center in Strasbourg, France.

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

M2CAI Workflow Dataset

1 of 8 classes for each frames :

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

M2CAI Workflow Goal and Measure

Goal : Multi-class classification

- Online prediction : $P(y_i|x_i, x_{i-1}, x_{i-2}, ...)$
  x_i := frame i, and y_i := class of frame i

Algorithm useful to

- Monitor surgeons
- Trigger automatic actions

Evaluation metrics

- **Jaccard index** : $J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A|+|B|-|A \cap B|}$
- Accuracy top1 : nb frames well classified / nb total frames

Two fold approach

1. Frames classifier using Deep Learning (Lib : Torch7)

- From Scratch Convolutional Neural Network (CNN) [1]
- Features Extraction CNN [1]
- Fine tuning CNN [1]

2. Smoothing predictions (Lib : Scikit-Learn)

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

1. Optimized with Adam [Kingma et Ba 2014]

Creating a trainset and valset of images

Creating validation set by random split

- 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

Training CNN From Scratch

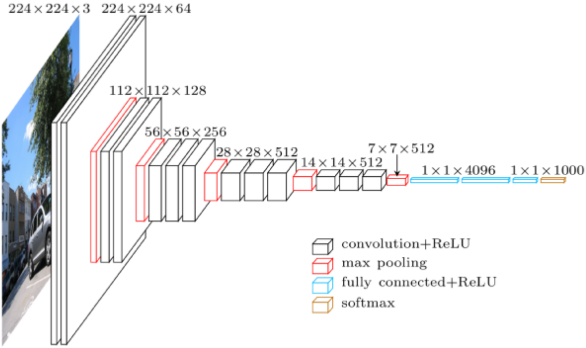
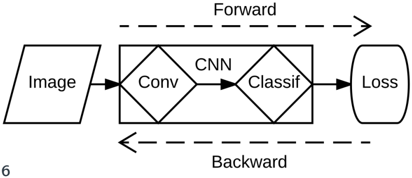
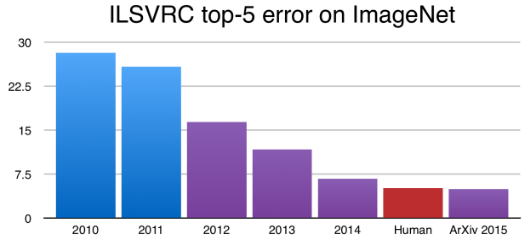


Figure 2: Vgg16 [Karen Simonyan et Zisserman 2014], top2 ILSVRC2014



ImageNet : 1.2M training images, 1000 classes



Using representations learned on ImageNet

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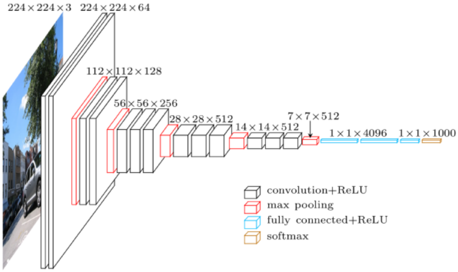
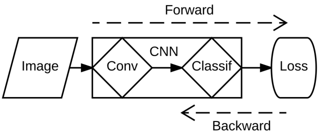
Pre-trained CNN as Features Extractor

1. Extracting features somewhere
2. Training a Support Vector Machine

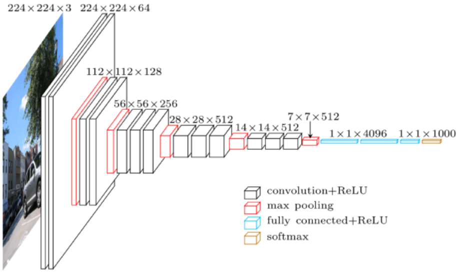


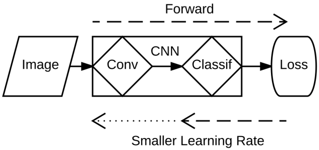


Adapting representations learned on Imagenet

Fine tuning a pre-trained CNN

- Same process than CNN From Scratch
- But smaller learning rate for pre-trained layers





Which CNN to use ? Possible in production ?

Model	Input	Param.	Depth	Implem.	Forward (ms)	Backward (ms)
Vgg16	224	138M	16	GPU	185.29	437.89
InceptionV3 [2]	399	24M	42	GPU	**102.21**	311.94
ResNet-200 [3]	224	65M	200	GPU	273.85	687.48
InceptionV3	399	24M	42	CPU	19918.82	23010.15

Table 1: Forward+Backward with batches of 20 images.

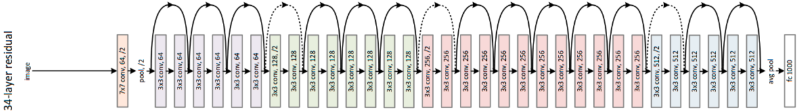
Possible in production thanks to GPUs !

2. [Szegedy et al. 2015]
3. [He et al. 2016]

Comparison of frames classifiers

Model	Type	Accuracy (%)
InceptionV3	Extraction (repres. of ImageNet)	60.53
InceptionV3	From Scratch (repres. of M2CAI)	69.13
InceptionV3	Fine-tuning (both representations)	79.06
ResNet200	**Fine-tuning (both representations)**	**79.24**

Table 2: Accuracy on the validation set.



Gaussian Hidden Markov Model

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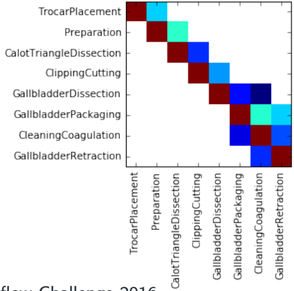
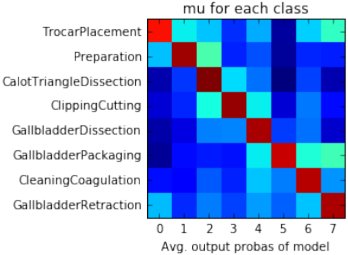
HMM on the smoothed predictions over last 15 frames

- Initial state probabilities :
- Matrix of probabilities of transition between states
- Gaussian parameters for emissions of observations :
  $\rightarrow$ mean and co-variance matrix





Gaussian Hidden Markov Model

Training process

- Counting using the training set annotations
- Counting using the predictions

Testing process

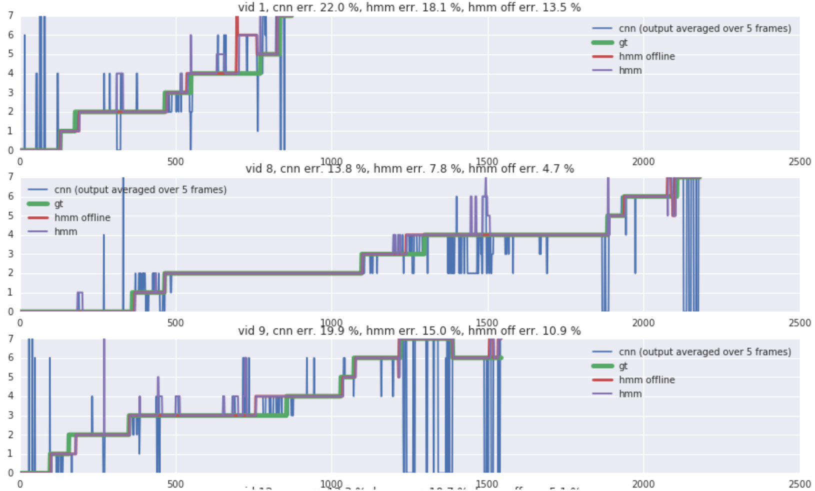
- Offline testing : Viterbi algorithm to obtain the most likely sequence of states
- **Online testing** : to predict x_t we apply Viterbi on the sequence $y_1, \ldots, y_t$

Comparison of temporal smoothing methods

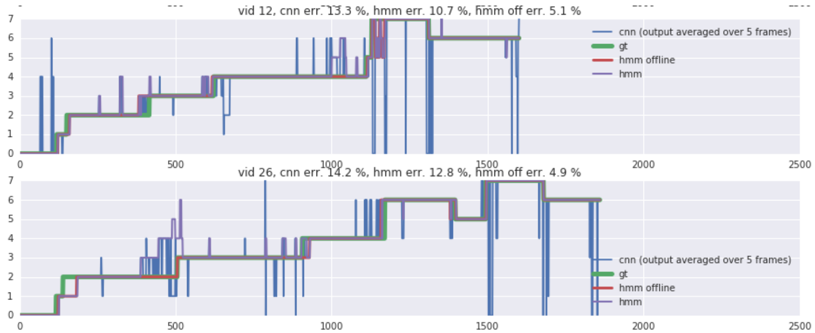
Temporal Method	Accuracy Val (%)	Jaccard Val	Jaccard Test
No Smoothing	79.24	–	–
Avg Smoothing	85.97	74.67	–
Avg + HMM Online	**88.90**	**81.60**	**71.9**
Avg + HMM Offline	93.47	87.59	–

Table 3: With the predictions of our fine tuned ResNet-200

Visualization



Visualization



Conclusion

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- Deep Learning efficient even without medical knowledge
- Fine Tuning most accurate approach
- HMM is usefull to smooth the predictions

Future work

- Fine tuning CNN on full trainset (not only 80%)
- Ensembling several fine tuned CNNs

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

References I

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