Master in Computer Vision *Barcelona*

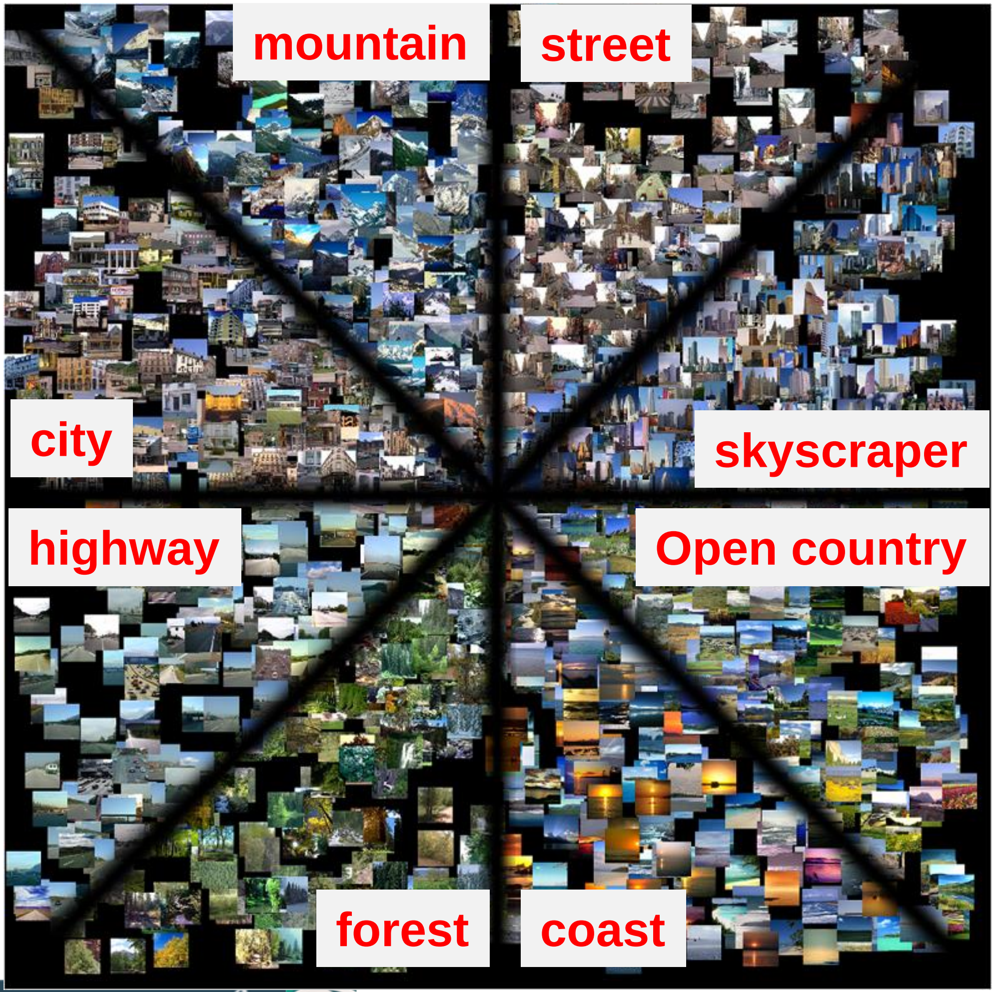
Module 3: Machine Learning for Computer Vision

Project: Deep learning classification

Lecturer: Ramon Baldrich

Module Goal

The aim of this module is to learn the techniques for category classification: handcrafted and learned.



The dataset

8 classes

Coast
244 train
116 test

Forest
227 train
101 test

Highway
184 train
76 test

Inside city
214 train
94 test

Mountain
260 train
114 test

Open country
292 train
118 test

Street
212 train
80 test

Tall building
248 train
108 test

Artificial Intellingence in Computer Vision

Machine learning for image classification:

- Handcrafted methods: Bag of Words: 2 sessions
- Data driven methods: Deep Convolutional Networks: 3 sessions

Artificial Intellingence in Computer Vision

Machine learning for image classification:

- Handcrafted methods: Bag of Words: 2 sessions
  - The Bag of Visual Words framework
  - Beyond BoVW: SVMs, Spatial Pyramids, Fisher Vectors

Artificial Intellingence in Computer Vision

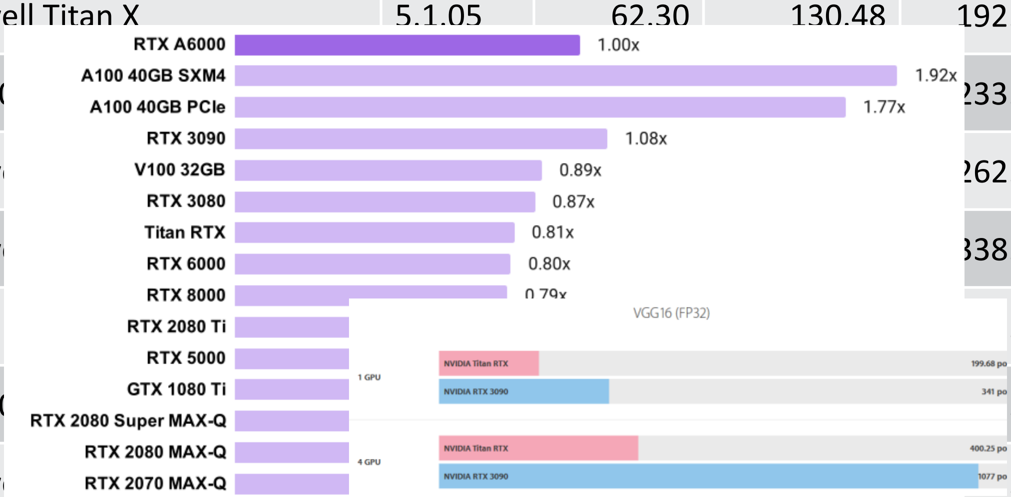
Machine learning for image classification:

- Data driven methods: Deep Convolutional Networks:
  - From hand-crafted to learnt features
  - Fine tuning of pre-trained CNNs
  - Training a CNN from scratch

Hardware available

VGG-16
(input 16 x 3 x 224 x 224)

GPU	cuDNN	Forward (ms)	Backward (ms)	Total (ms)
Pascal Titan X	5.1.05	41.59	87.03	128.62
Pascal Titan X	5.0.05	46.16	111.23	157.39
GTX 1080	5.1.05	59.37	123.42	182.79
Maxwell Titan X	5.1.05	62.30	130.48	192.78
GTX 1(				233.43
Maxw				262.27
Maxw				338.69
Pascal				.53
GTX 1(				.82
Maxw				.47
CPU: Dual Xeon E5-2630 v3	None	3101.76	5393.72	8495.48



RTX 3090

TITAN X (pascal)

GTX 1080 Ti

~1 per group.

https://github.com/jcjohnson/cnn-benchmarks

Libraries

- Standard libraries:
  - Python + common libraries
  - Numpy + sklearn

- Specialized libraries:
  - Keras (Tensorflow)
  - Pytorch
  - JAX
  - ...

GPU server: User Installation and Usage Manual

- **Connect to the server** Instructions in virtual campus

  ssh to 158.109.75.50 –p 22 (3090's server)

  ssh to 158.109.75.51 –p 22 (TitanX's server)

  users/psswd : group01 … group10 / 01group … 10group

- **Mount your server folder in your local computer to edit locally**
- **Create a permanent connection to the server (Your process will continue working even if the connection to the server is lost)**

  # Connect to the server via ssh

  # Run screen command to create a new connection screen

  $ screen or $ byobu

Code, installing instructions and dataset in ~/mcv,
Queue managment in ~/example

GPU server: User Installation and Usage Manual

Environtment installation

$ bash ~/mcv/Anaconda3-20XX????-Linux-x86_64.sh

yes to all ....

exit/login

$conda install -c anaconda pydot

add the following two lines at the end of file .bashrc

export LD_LIBRARY_PATH=/usr/local/cuda/lib64:$LD_LIBRARY_PATH

export CUDA_HOME=/usr/local/cuda

$ conda install tensorflow-gpu

$ conda install keras

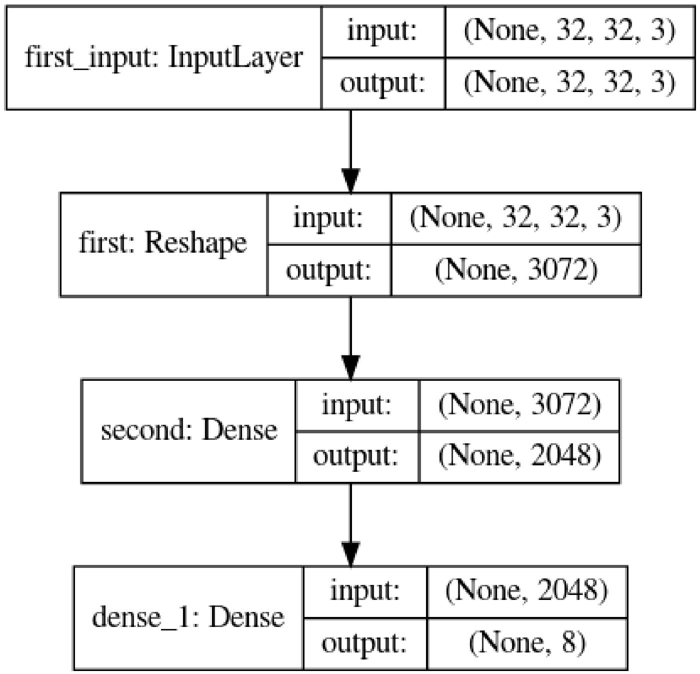
GPU server: User Installation and Usage Manual

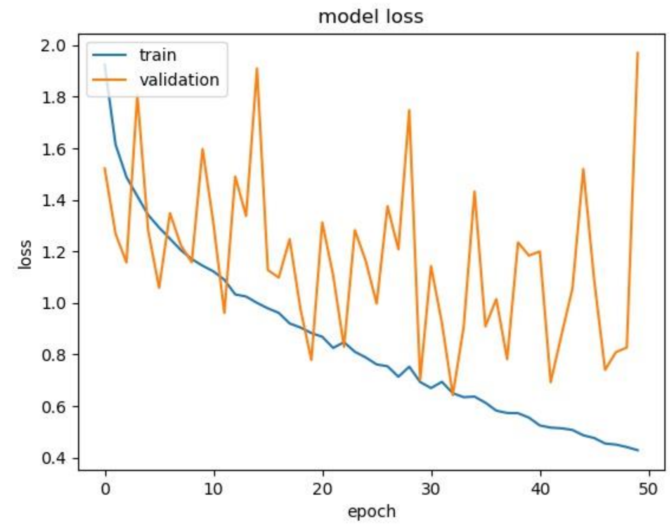
- Check gpu status: nvidia-smi

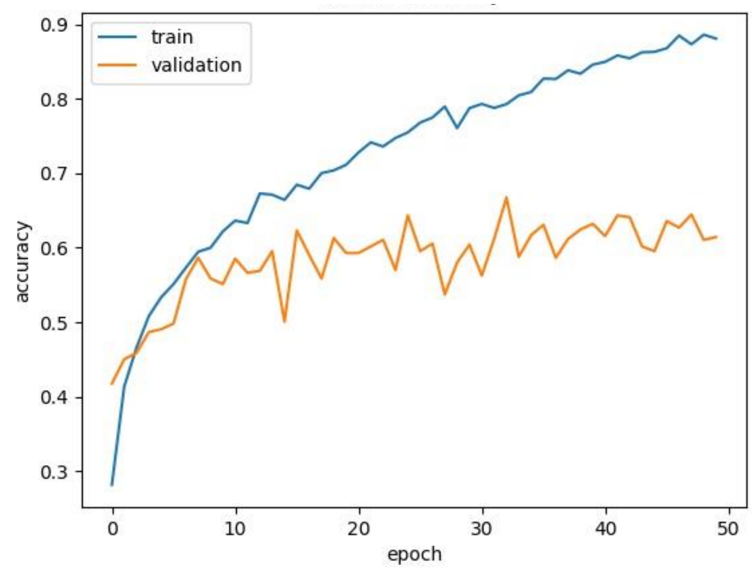
```
master@mastergpu01:~$ nvidia-smi
Wed Jan 18 13:46:18 2017
+------------------------------------------------------------------------------+
| NVIDIA-SMI 367.57                 Driver Version: 367.57                     |
|-------------------------------+----------------------+------------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  TITAN X (Pascal)    Off  | 0000:0B:00.0     Off |                  N/A |
| 40%   70C    P2   157W / 250W |  11705MiB / 12189MiB |     57%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID  Type  Process name                               Usage      |
|=============================================================================|
|    0      8647    C   python                                      11703MiB |
+-----------------------------------------------------------------------------+
master@mastergpu01:~$
```

- Run your first code:
  copy 'job' file & *.py files to your working folder
  Edit mlp_MIT_8_scene.py to fit your working folder.
  $ sbatch job

GPU server: User Installation and Usage Manual

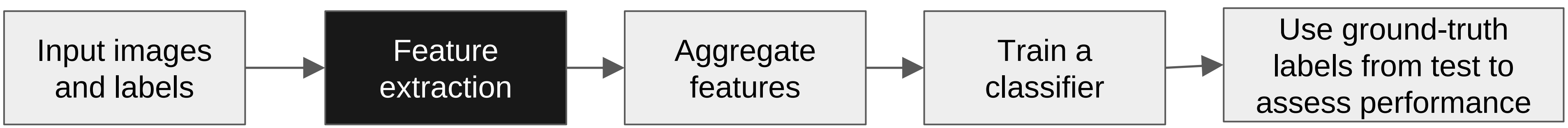




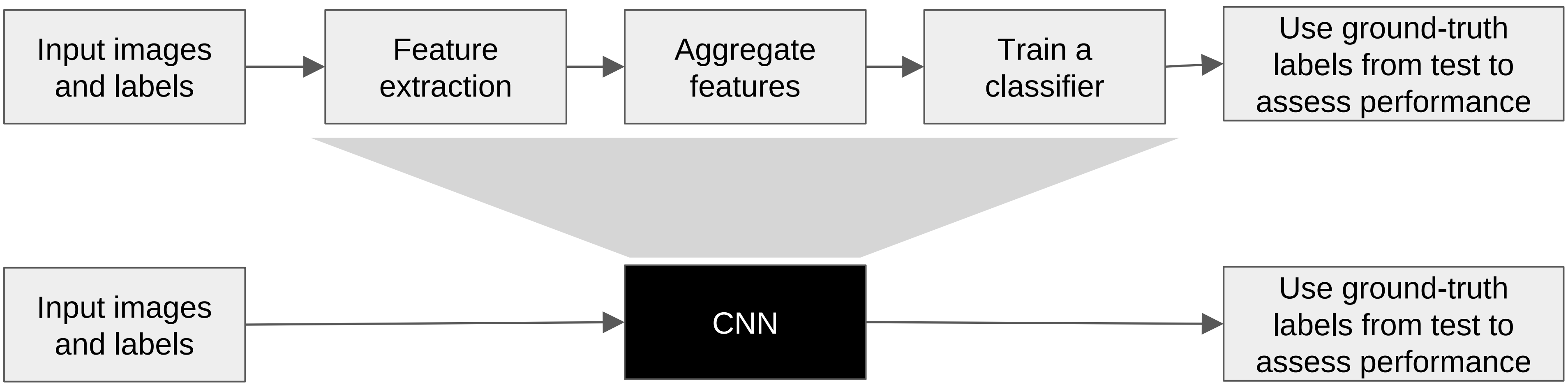


We need something more clever

Pipeline of the project W3



Pipeline of the project W4 and W5



End to end task

Keras: first example

```
# create model
model = Sequential()
model.add(Dense(12, input_dim=8, init='uniform', activation='relu'))
model.add(Dense(8, init='uniform', activation='sigmoid'))

inputs = Input(shape=None))
x = Dense(12, init='uniform', activation='relu', name='fc1')(x)
x = Dense(8, init='uniform', activation='sigmoid', name= 'predictions')(x)
model = Model(inputs, x, name='example')
```

W3-5

```
# Compile model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
# Fit the model
model.fit(X, Y, nb_epoch=150, batch_size=10)
# evaluate the model
scores = model.evaluate(X, Y)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

W3-4

```
# predict with the model
features = model.predict(X)
```

W3-4

https://keras.io/api/

Keras

Star 57,089

Search Keras documentation...

Keras API reference

Models API

- The Model class
- The Sequential class
- Model training APIs
- Model saving & serialization APIs

Layers API

- The base Layer class
- Layer activations
- Layer weight initializers
- Layer weight regularizers
- Layer weight constraints
- Core layers
- Convolution layers
- Pooling layers
- Recurrent layers
- Preprocessing layers
- Normalization layers
- Regularization layers
- Attention layers
- Reshaping layers
- Merging layers
- Locally-connected layers
- Activation layers

Callbacks API

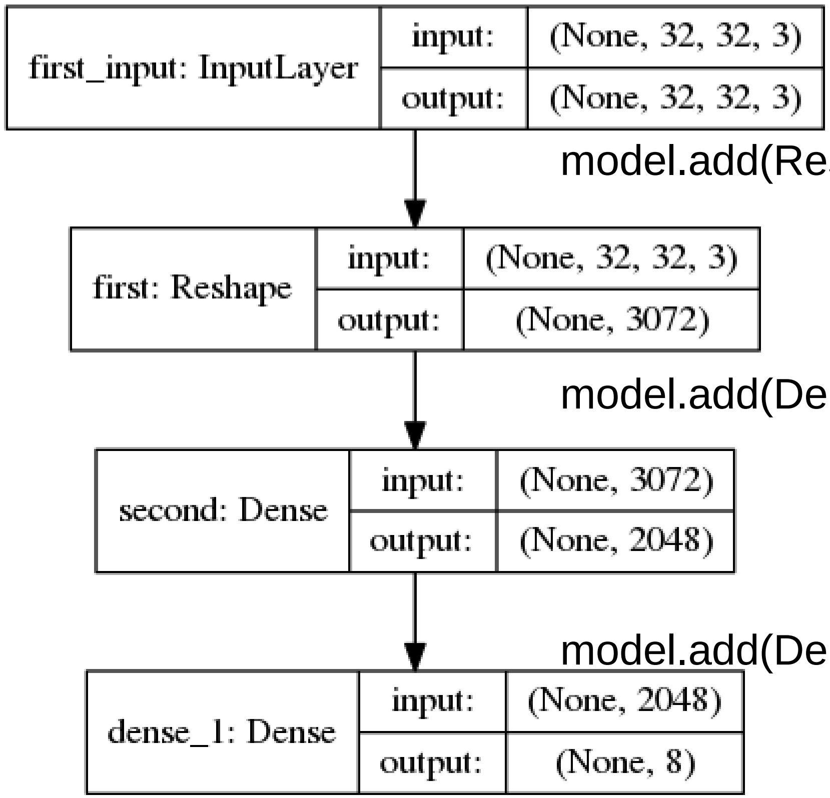
- Base Callback class
- ModelCheckpoint
- BackupAndRestore

Week 3: learnt features in Bow

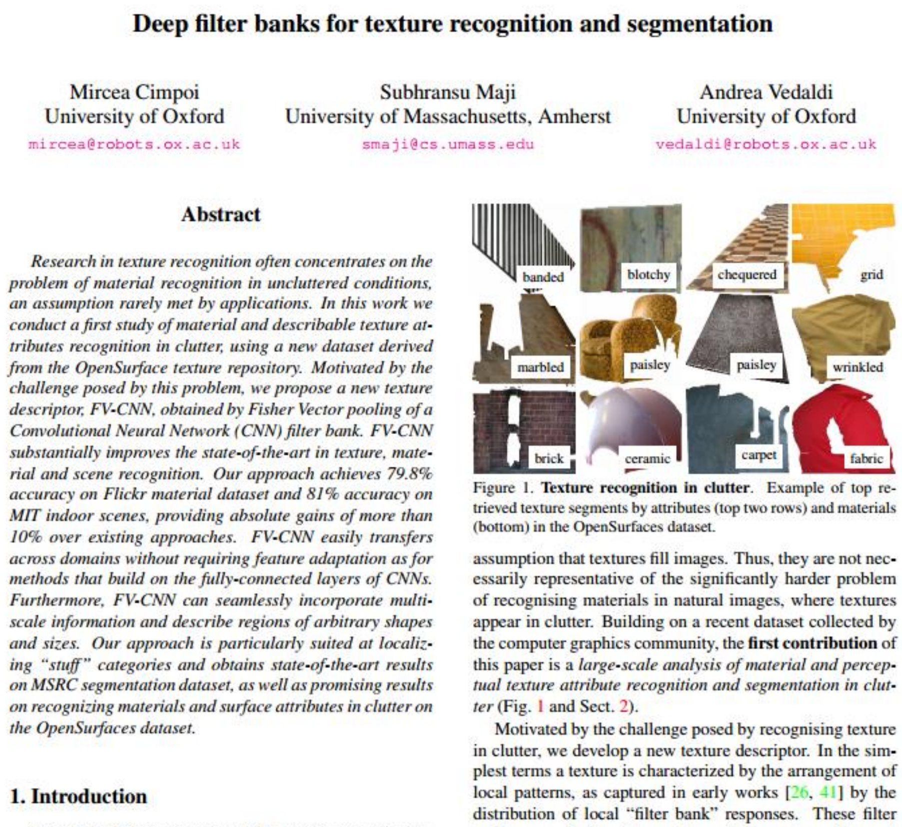
Goals:

- Understand MLP topology
- Learn to extract features from a network
- Compare learnt features with handcrafted fetaures

```
model = Sequential()
model.add(Reshape((32*32*3,),input_shape=(32, 32, 3),name='first'))
model.add(Dense(units=2048, activation='relu', name='second'))
model.add(Dense(units=8, activation='softmax'))
```



Use feature maps as learnt descriptor



Deep filter banks for texture recognition and segmentation

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Abstract

Research in texture recognition often concentrates on the problem of material recognition in uncluttered conditions, an assumption rarely met by applications. In this work we conduct a first study of material and describable texture attributes recognition in clutter, using a new dataset derived from the OpenSurface texture repository. Motivated by the challenge posed by this problem, we propose a new texture descriptor, FV-CNN, obtained by Fisher Vector pooling of a Convolutional Neural Network (CNN) filter bank. FV-CNN substantially improves the state-of-the-art in texture, material and scene recognition. Our approach achieves 79.8% accuracy on Flickr material dataset and 81% accuracy on MIT indoor scenes, providing absolute gains of more than 10% over existing approaches. FV-CNN easily transfers across domains without requiring feature adaptation as for methods that build on the fully-connected layers of CNNs. Furthermore, FV-CNN can seamlessly incorporate multi-scale information and describe regions of arbitrary shapes and sizes. Our approach is particularly suited at localizing "stuff" categories and obtains state-of-the-art results on MSRC segmentation dataset, as well as promising results on recognizing materials and surface attributes in clutter on the OpenSurfaces dataset.

1. Introduction

Texture is ubiquitous and provides useful cues of mate-

Figure 1. **Texture recognition in clutter**. Example of top retrieved texture segments by attributes (top two rows) and materials (bottom) in the OpenSurfaces dataset.

assumption that textures fill images. Thus, they are not necessarily representative of the significantly harder problem of recognising materials in natural images, where textures appear in clutter. Building on a recent dataset collected by the computer graphics community, the **first contribution** of this paper is a *large-scale analysis of material and perceptual texture attribute recognition and segmentation in clutter* (Fig. 1 and Sect. 2).

Motivated by the challenge posed by recognising texture in clutter, we develop a new texture descriptor. In the simplest terms a texture is characterized by the arrangement of local patterns, as captured in early works [26, 41] by the distribution of local "filter bank" responses. These filter

- Extract features
- Agregate channels
  - Statistics
  - Dimensioanlity reduction
- Apply BoW/Fisher
- Apply classifier

Cimpoi, M., Maji, S., & Vedaldi, A. (2015). Deep filter banks for texture recognition and segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3828-3836).

Experimentation

- MLP on small images: end to end vs svm
- MLP as dense descriptor: end to end vs BoW

Experimentation

MLP on small images: end to end vs svm

- Redefine the structure of the newtork (adding new layers, changing image size, …)
- Extract the output from a given layer as descriptor and apply svm on it

Experimentation

MLP as dense descriptor: end to end vs BoW

- Divide the image into small patches
- Extract the prediction for each patch, and agregate the final prediction (end to end)
- Take each patch output, given a layer, as a dense descriptor and apply Bow

utils.py
mlp_MIT_8_scene.py
patch_based_mlp_MIT_8_scene.py

Code

Creating a Network

```
model = Sequential()
model.add(Reshape((IMG_SIZE*IMG_SIZE*3,),input_shape=(IMG_SIZE, IMG_SIZE, 3),name='first'))
model.add(Dense(units=2048, activation='relu',name='second'))
model.add(Dense(units=8, activation='softmax'))

model.compile(loss='categorical_crossentropy',
          optimizer='sgd',
          metrics=['accuracy’])
```

<u>Sub model</u>

```
model2 = Model(input=model.input, output=base_model.get_layer(‘second').output)
features = model2.predict(x)
```

Feeding data to the network

Code

```
train_datagen = ImageDataGenerator(
    rescale=1./255,
    horizontal_flip=True)

test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    DATASET_DIR+'/train',  # this is the target directory
    target_size=(IMG_SIZE, IMG_SIZE),  # all images will be resized to IMG_SIZExIMG_SIZE
    batch_size=BATCH_SIZE,
    classes = ['coast','forest','highway','inside_city','mountain','Opencountry','street','tallbuilding'],
    class_mode='categorical')  # since we use binary_crossentropy loss, we need categorical labels

# this is a similar generator, for validation data
validation_generator = test_datagen.flow_from_directory(
    DATASET_DIR+'/test',
    target_size=(IMG_SIZE, IMG_SIZE),
    batch_size=BATCH_SIZE,
    classes = ['coast','forest','highway','inside_city','mountain','Opencountry','street','tallbuilding'],
    class_mode='categorical')
```

Code

Training the network

```
history = model.fit(
    train_generator,
    steps_per_epoch=1881 // BATCH_SIZE,
    epochs=50,
    validation_data=validation_generator,
    validation_steps=807 // BATCH_SIZE)
```

Getting predictions from inner layers

```
model_layer = Model(input=model.input, output=model.get_layer('second').output)
#get the features from images
features = model_layer.predict(x)
```

Code

How to plot learning curves

```
 # summarize history for accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.savefig('accuracy.jpg')
plt.close()
 # summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.savefig('loss.jpg')
```

Tasks

Understanding network topoplogy

1. Add/change layers in the network topology
2. Given an image, get the output of a given layer
3. Manage to merge multiple outputs from a single image in an end to end network

Compare learnt features vs handcrafted features

4. Extract a single feature from an input and apply to svm, compare to end to end network
5. Extract multiple features from an image and apply BoW, compare to end to end network

Grades, deliverables and deadline

- Deliver source code and a **short** slide presentation of the work done
  - For each task, all the carried tests with their associated results
  - 1 slide summarizing the best yielded result and configuration for each task
- Should be delivered by Monday 23th at <u>10:30AM</u>