

# unmixing

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If you plan on using this implementation, please cite our work:

@INPROCEEDINGS{Tulczyjew2021IGARSS, author={Tulczyjew, Lukasz and Nalepa, Jakub}, booktitle={IGARSS 2021 - 2021 IEEE International Geoscience and Remote Sensing Symposium}, title={Investigating the impact of the training set size on deep learning-powered hyperspectral unmixing}, year={2021}, note={in press}}

## 1 Parameters description for the unmixing experiments

Train and evaluate the convolutional neural network (CNN) as well as the deep convolutional autoencoder (DCAE) for the unmixing problem. Exemplary hyperparameters to set:

- `-data-file-path` - path to the hyperspectral image (HSI).
- `-ground-truth-path` - path to the ground truth map containing the fractions of abundances for entire HSI.
- `-train-size` - magnitude of the learning set that is utilized to fine-tune the weights of the model.
- `-sub-test-size` - size of the test set to evaluate the generalization of the model. It is sampled from the remaining HSI excluding the training subset. If not specified, all non-training samples constitute the test set. Can be employed in the case of experiments when changing the magnitudes of training sets while keeping the size of testing sets constant.
- `-val-size` - fraction or size of the validation subset, it is designed to monitor the overfitting.
- `-channels-idx` - index of the spectral dimension in input HSI.
- `batch-size` - number of samples per update step in the training phase.
- `-shuffle` - indicates whether to shuffle the dataset in experiment.
- `-patience` - stopping condition for a specific number of epochs without improvement.
- `-model-name` - name of the utilized model, exemplary values: `unmixing_pixel_based_cnn`, `unmixing_cube_based_cnn`, `unmixing_pixel_based_dcae`, `unmixing_cube_based_dcae` for the pixel-based, cube-based CNN and DCAE respectively.
- `-sample-size` - number of spectral bands in a given HSI.
- `-neighborhood-size` - size of the spatial extent which is employed for each sample in the form of local neighboring pixels. Most cases allows to leverage the quality of the segmentation as well as the unmixing.
- `-n-classes` - number of endmembers in the HSI for which the abundances will be estimated by the model.
- `-lr` - learning rate regulates the step size during weights updates in the training phase.
- `-epochs` - second stopping condition, i.e., the maximum number of epochs.
- `-verbose` - verbosity mode.

- `-save-data` - indicates whether to save the training and test data.

## 2 Cube-based DCAE

We specify the necessary parameters for the experiment.

```
[1]: # Execute cube-based DCAE:
from os.path import join

base_path = r'../datasets/urban'
data_file_path = join(base_path, 'urban.npy')
ground_truth_path = join(base_path, 'urban_gt.npy')
endmembers_path = join(base_path, 'urban_m.npy')
train_size = 15500
sub_test_size = 47249
val_size = 0.1
channels_idx = -1
batch_size = 256
shuffle = True
patience = 3
model_name = 'unmixing_cube_based_dcae'
sample_size = 162
neighborhood_size = 5
n_classes = 6
dest_path = join('../examples', 'unmixing_results')
lr = 0.0005
epochs = 10
verbose = 0
save_data = False
use_mlflow = False
seed = 1

[2]: import os
import warnings
warnings.filterwarnings('ignore')

import tensorflow as tf

from ml_intuition import enums
from ml_intuition.data.utils import parse_train_size, subsample_test_set, \
    plot_training_curve, show_statistics
from scripts import prepare_data
from scripts.unmixing import train_unmixing, evaluate_unmixing

os.makedirs(dest_path, exist_ok=True)
```

```
dcae_dest_path = join(dest_path, 'cube-based-dcae')
os.makedirs(dcae_dest_path, exist_ok=True)
```

### 3 Prepare data

We prepare data for the unmixing by utilizing the *prepare\_data.main* method. It accepts various parameters such as path to the data file or ground-truth for a specific HSI. Furthermore, magnitude of the learning set can be also specified. Moreover, the method accepts the neighborhood size parameter, which specifies the spatial extent of each sample. For each run in the experiment, for the sake of reproducibility, it is possible to set a specific seed. The returned object is a dictionary with three keys: *train*, *test* and *val*. Each of them contains an additional dictionary with *data* and *labels* keys, holding corresponding *numpy.ndarray* objects with the data. For more details about the parameters, refer to the documentation of *prepare\_data.main* function (located in *scripts/prepare\_data*).

```
[3]: # Prepare data for unmixing:
data = prepare_data.main(data_file_path=data_file_path,
                        ground_truth_path=ground_truth_path,
                        train_size=parse_train_size(train_size),
                        val_size=val_size,
                        stratified=False,
                        background_label=-1,
                        channels_idx=channels_idx,
                        neighborhood_size=neighborhood_size,
                        save_data=save_data,
                        seed=seed,
                        use_unmixing=True)

# Subsample the test set to constitute a constant size:
if sub_test_size is not None:
    subsample_test_set(data[enums.Dataset.TEST], sub_test_size)
```

### 4 Train and evaluate the model

Few parameters previously initialized are employed in this step e.g., the name of the model, size of the spectral extent, learning rate and batch size. The results including the metrics are stored in *dcae\_dest\_path* directory.

```
[4]: # Train the model:
train_unmixing.train(model_name=model_name,
                    dest_path=dcae_dest_path,
                    data=data,
                    sample_size=sample_size,
                    neighborhood_size=neighborhood_size,
                    n_classes=n_classes,
```

```

lr=lr,
batch_size=batch_size,
epochs=epochs,
verbose=verbose,
shuffle=shuffle,
patience=patience,
endmembers_path=endmembers_path,
seed=seed)
# Evaluate the model:
evaluate_unmixing.evaluate(
    model_path=os.path.join(dcae_dest_path, model_name),
    data=data,
    dest_path=dcae_dest_path,
    neighborhood_size=neighborhood_size,
    batch_size=batch_size,
    endmembers_path=endmembers_path)
tf.keras.backend.clear_session()

```

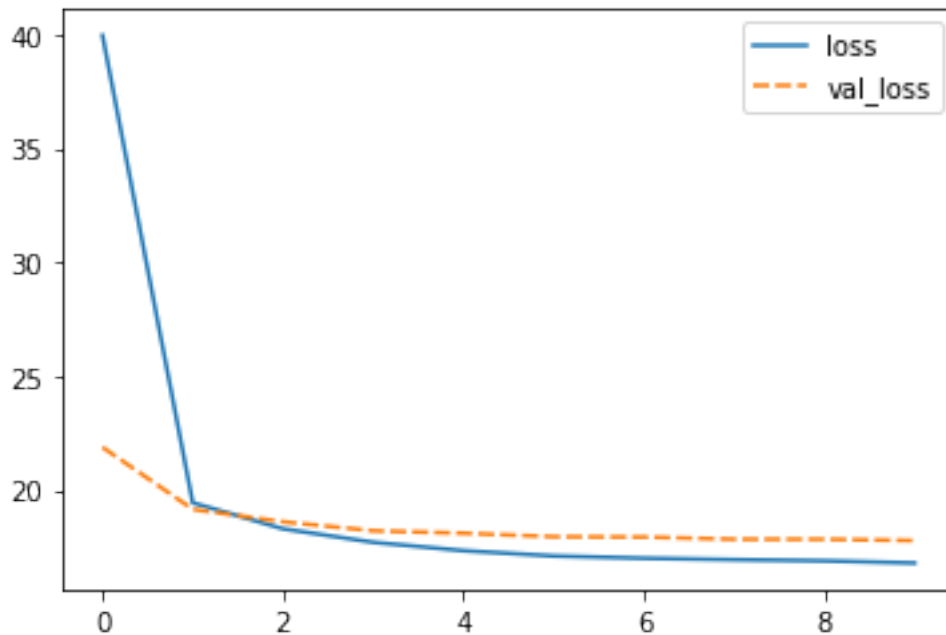
c:\users\lukasz\desktop\machine-learning\venv\lib\site-packages\tensorflow\python\framework\tensor\_util.py:125: DeprecationWarning: np.asscalar(a) is deprecated since NumPy v1.16, use a.item() instead  
 tensor\_proto.float\_val.extend([np.asscalar(x) for x in proto\_values])

Layer (type)	Output Shape	Param #
conv3d (Conv3D)	(None, 3, 3, 160, 16)	448
conv3d_1 (Conv3D)	(None, 1, 1, 158, 32)	13856
conv3d_2 (Conv3D)	(None, 1, 1, 156, 64)	6208
conv3d_3 (Conv3D)	(None, 1, 1, 154, 128)	24704
flatten (Flatten)	(None, 19712)	0
dense (Dense)	(None, 256)	5046528
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 6)	1542
softmax (Softmax)	(None, 6)	0
dense_2 (Dense)	(None, 162)	1134

Total params: 5,094,420  
 Trainable params: 5,093,286

Non-trainable params: 1,134

```
[5]: plot_training_curve(os.path.join(dcae_dest_path, 'training_metrics.csv'),
                        curve_names=['loss', 'val_loss'],
                        y_limit=False)
show_statistics(os.path.join(dcae_dest_path, 'inference_metrics.csv'))
```



```
[5]:      aRMSE      aSAM  overallRMSE    rmsAAD  perClassSumRMSE  classORMSE  \
0  0.052665  0.167482    0.080721  0.285665    0.474069    0.085252

      class1RMSE  class2RMSE  class3RMSE  class4RMSE  class5RMSE    rRMSE  \
0  0.102679    0.083158    0.052504    0.087284    0.063191  0.060676

      rSID  inference_time
0  3085.67749    28.327313
```

## 5 Pixel-based CNN

We perform the same steps for the pixel-based CNN model, however a few parameters must be altered. Since we utilize only the spectral dimension, the *neighborhood\_size* is set to *None*, the learning rate is also adjusted. The *endmembers\_path* is also not needed anymore, since we train the model on the fractions of abundances of each endmember. The pipeline looks similar to the DCAE model.

```

[6]: # Execute the pixel-based CNN:
endmembers_path = None
model_name = 'unmixing_pixel_based_cnn'
lr = 0.01
neighborhood_size = None
cnn_dest_path = join(dest_path, 'pixel-based-cnn')
os.makedirs(cnn_dest_path, exist_ok=True)

# Prepare data for unmixing:
data = prepare_data.main(data_file_path=data_file_path,
                        ground_truth_path=ground_truth_path,
                        train_size=parse_train_size(train_size),
                        val_size=val_size,
                        stratified=False,
                        background_label=-1,
                        channels_idx=channels_idx,
                        neighborhood_size=neighborhood_size,
                        save_data=save_data,
                        seed=seed,
                        use_unmixing=True)

# Subsample the test set to constitute a constant size:
if sub_test_size is not None:
    subsample_test_set(data[enums.Dataset.TEST], sub_test_size)

# Train the model:
train_unmixing.train(model_name=model_name,
                    dest_path=cnn_dest_path,
                    data=data,
                    sample_size=sample_size,
                    neighborhood_size=neighborhood_size,
                    n_classes=n_classes,
                    lr=lr,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=verbose,
                    shuffle=shuffle,
                    patience=patience,
                    endmembers_path=endmembers_path,
                    seed=seed)

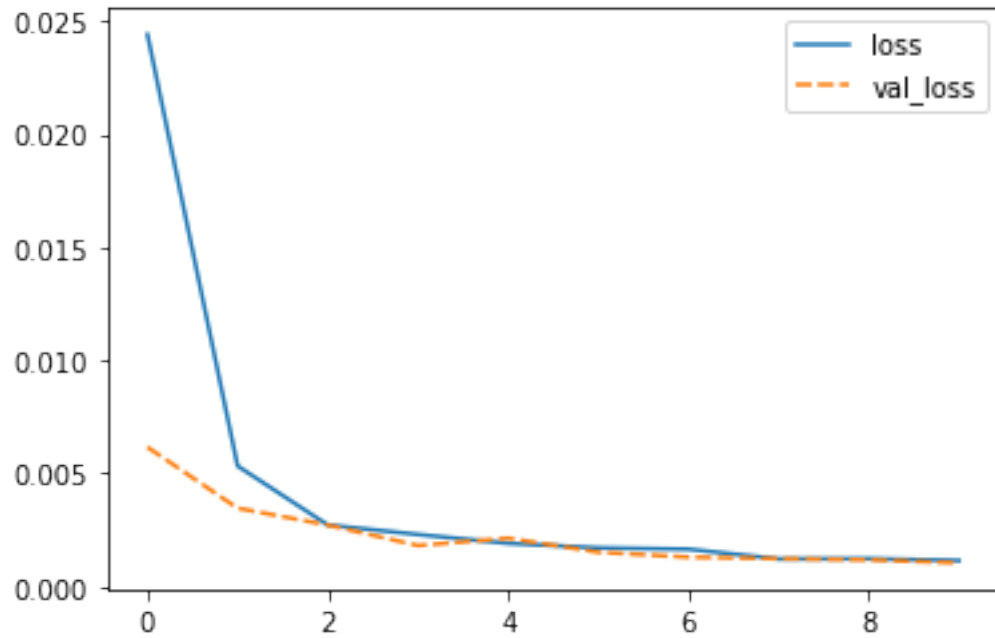
# Evaluate the model:
evaluate_unmixing.evaluate(
    model_path=os.path.join(cnn_dest_path, model_name),
    data=data,
    dest_path=cnn_dest_path,
    neighborhood_size=neighborhood_size,
    batch_size=batch_size,
    endmembers_path=endmembers_path)
tf.keras.backend.clear_session()

```

```
c:\users\lukasz\desktop\machine-learning\venv\lib\site-
packages\tensorflow\python\framework\tensor_util.py:125: DeprecationWarning:
np.asscalar(a) is deprecated since NumPy v1.16, use a.item() instead
    tensor_proto.float_val.extend([np.asscalar(x) for x in proto_values])
```

Layer (type)	Output Shape	Param #
conv3d (Conv3D)	(None, 1, 1, 158, 3)	18
max_pooling3d (MaxPooling3D)	(None, 1, 1, 79, 3)	0
conv3d_1 (Conv3D)	(None, 1, 1, 76, 6)	78
max_pooling3d_1 (MaxPooling3D)	(None, 1, 1, 38, 6)	0
conv3d_2 (Conv3D)	(None, 1, 1, 34, 12)	372
max_pooling3d_2 (MaxPooling3D)	(None, 1, 1, 17, 12)	0
conv3d_3 (Conv3D)	(None, 1, 1, 14, 24)	1176
max_pooling3d_3 (MaxPooling3D)	(None, 1, 1, 7, 24)	0
flatten (Flatten)	(None, 168)	0
dense (Dense)	(None, 192)	32448
dense_1 (Dense)	(None, 150)	28950
dense_2 (Dense)	(None, 6)	906
Total params: 63,948		
Trainable params: 63,948		
Non-trainable params: 0		

```
[7]: plot_training_curve(os.path.join(cnn_dest_path, 'training_metrics.csv'),
    curve_names=['loss', 'val_loss'],
    y_limit=False)
    show_statistics(os.path.join(cnn_dest_path, 'inference_metrics.csv'))
```



```
[7]:      aRMSE      aSAM  overallRMSE    rmsAAD  perClassSumRMSE  classORMSE  \
0  0.023885  0.073451    0.032043  0.109212    0.189771    0.037084

      class1RMSE  class2RMSE  class3RMSE  class4RMSE  class5RMSE  inference_time
0  0.036499    0.033178    0.024482    0.024789    0.033738    1.865043
```