EagleEyes_Germany

January 6, 2022

1 AI4Food Security South Africa

Team EagleEyes:

Christina Bukas, HMGU
Frauke Albrecht, DKRZ
Caroline Arnold, DKRZ

We would also like to thank Elisabeth Georgii from HMGU for her contribution in literature research and useful insights when discussing methods

1.1 Introduction

The aim of this challenge is to identify crop types in-season using Planet, Sentinel-1, and Sentinel-2 data. Field boundaries and cropy type labels are given as ground truth data.

1.2 Setup

In the following cell, all modules are imported that are necessary in this notebook.

[1]:
```
import os
import copy

import h5py
import numpy as np
import geopandas as gpd

import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset
```

1.3 Data exploration

1.3.1 Preprocessing

Data from Planet, Sentinel-1, and Sentinel-2 satellites are given for a region in Germany. We process the datasets individually, building on the routines that were provided through the starter notebook. The workflow is described here for Planet data.

1. Rasterize the satellite images using the provided routines, for each field save a zip file containing the time series of bands and the mask
2. Load the field ID and apply custom data transform. Available transforms are: spatial average, crop image, extract fixed number of pixels
3. Save as `hdf5` files for use in training

The full preprocessing module is included in `dataloaders/preprocessor.py`, with the dataset readers in `dataloaders/custom_{planet,sentinel_1,sentinel_2}_reader.py` and the image transforms in `dataloaders/custom_data_transform.py`.

We generated the training data by running

```
python preprocessor.py --region germany --data-source planet --t-random-extraction
640 --n-processes 64 --target-sub-dir extracted-640 --overwrite
```

```
python preprocessor.py --region germany --data-source sentinel-1
--t-random-extraction 640 --n-processes 64 --target-sub-dir extracted-640
--overwrite
```

```
python preprocessor.py --region germany --data-source sentinel-2
--t-random-extraction 640 --n-processes 64 --target-sub-dir extracted-640
--overwrite
```

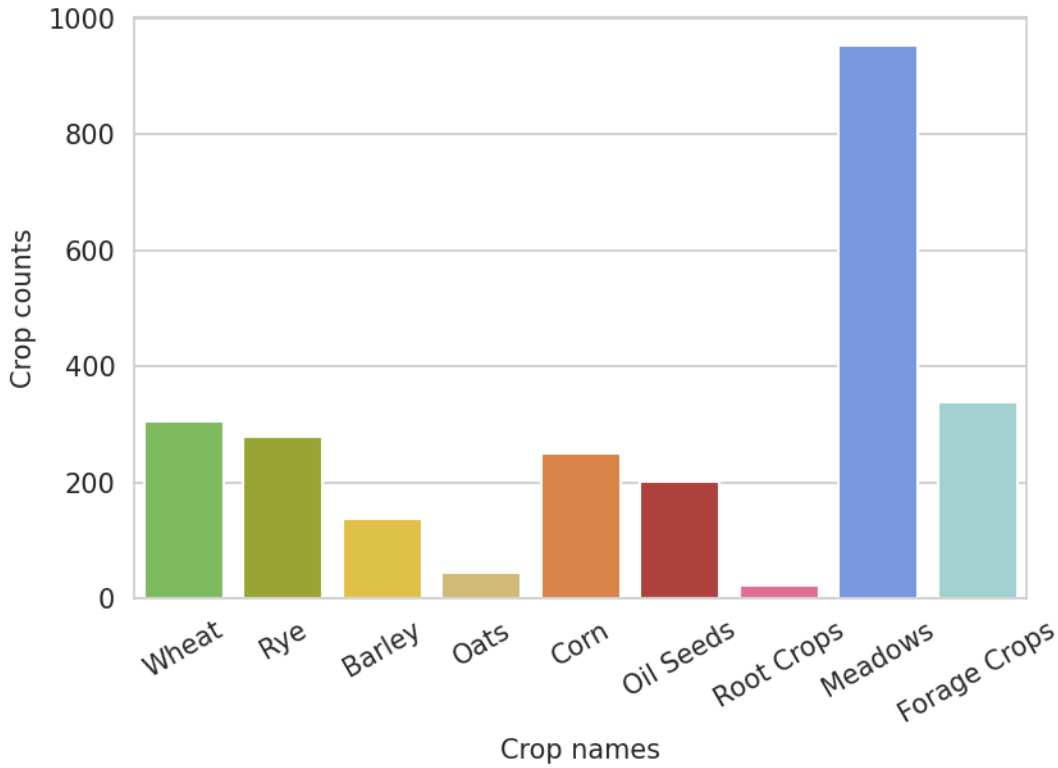
This extracts 640 pixels at random from a field, taking into account only the valid pixels as given by the mask. We resample if there are less than 640 pixels are available. Then, out of each field, we create 10 training samples, containing 64 extracted pixels each. Thus, we arrive at a total count of 21250 samples that can be used in training / validation. For the test set, 64 pixels are extracted at random per field.

1.3.2 Training and validation

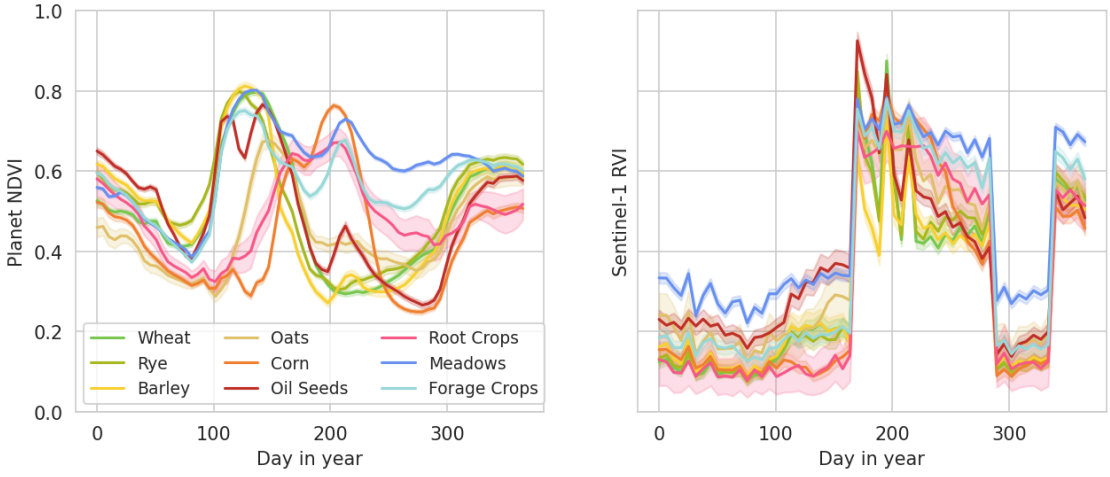
We use 10-fold cross validation, dividing the labeled data into training and validation set by field ID.

1.3.3 Exploration

The crop types are not evenly distributed:



We calculate the normalized vegetation index NDVI as the normalized difference of infrared and red planet data bands. Below (left) the average NDVI is shown throughout the growing season for the different crop types. For Sentinel-1 data, we calculate the Radar Vegetation Index (right), shown only for observations with the same angle. Note that the data includes observations in the early and late year, that are not strictly part of the growing season. We ended up using only the Planet dataset for this challenge track.



1.4 PSELTAE Model

The model used is discribed in detail in "Satellite Image Time Series Classification With Pixel-Set Encoders and Temporal Self-Attention", Garnot. et al. (2020) and the code has been adapted from

https://github.com/VSainteuf/pytorch-psetae. The model consists of a Spatial and a Temporal encoder. As spatial encoder a Pixel-Set Encoder is used, which uses as input a random set of pixels from each crop field. As Temporal Encoder, an attention based Neural Network is used. Data fusion with Sentinel-1 and Sentinel-2 data was explored by combining 2 (3) PseLTae models in the decoder stage, however, this did not improve the accuracy.

In order to train the model the datasets have been created by the following code:

[2]:
```
#!/usr/bin/env python

from torch.utils.data import Dataset
import h5py
import os
import numpy as np
import geopandas as gpd
from torch import randn
import time
from scipy.interpolate import splrep, splev
from scipy.signal import savgol_filter

class EarthObservationDataset(Dataset):
    '''
    Parent class for Earth Observation Datasets

    Preprocessed data is loaded from path:

    -- in args namespace --
      dev_data_dir    : file path on mistral, {germany, south africa}
      input_data[0]   : data source {planet, sentinel-1, sentinel-2}
      input_data_type : {extracted, extracted-640}
      split           : {train, test}

      If args.include_extras, the crop_area and crop_len are included for each␣
↪sample
    '''

    def __init__(self, args):
        super().__init__()
        self.args = args

        self.h5_file = h5py.File(os.path.join(args.dev_data_dir, args.
↪input_data[0], args.input_data_type, f'{args.split}_data.h5'), 'r')

        self.X = self.h5_file['image_stack'][:].astype(np.float32)
        self.mask = self.h5_file['mask'][:].astype(bool)
        self.fid = self.h5_file['fid'][:]
        self.labels = self.h5_file['label'][:]
```

```
        self.labels = self.labels - 1 # generated datafiles with classes from 1 .
↪.. k --> 0 ... k-1
        if np.sum(np.isnan(self.X)) > 0:
            print('WARNING: Filled NaNs and INFs with 0 in ', os.path.join(args.
↪dev_data_dir, args.input_data[0], args.input_data_type, f'{args.split}_data.
↪h5'))
            self.X = np.nan_to_num(self.X, nan=0, posinf=0, neginf=0)

        if args.include_extras:
            labels_path = os.path.join(args.dev_data_dir,'labels_combined.
↪geojson')
            print('Adding extra features from ', labels_path)
            extras = gpd.read_file(labels_path)

            crop_area = []
            crop_len  = []

            extras_fid = extras["fid"].values
            extras_crop_area = extras["NORMALIZED_SHAPE_AREA"].values
            extras_crop_len = extras["NORMALIZED_SHAPE_LEN"].values

            for ii, ffid in enumerate(self.fid):
                ix = np.where(extras_fid==ffid)[0][0]
                crop_area.append(extras_crop_area[ix])
                crop_len.append(extras_crop_len[ix])

                if ii%(len(self.fid)//20) == 0:
                    print(f'... finished {ii:8d}/{len(self.fid):8d} entries ({ii/
↪len(self.fid)*100:.1f} %)')

            self.extra_features = np.array([crop_area, crop_len]).T
        else:
            self.extra_features = None

        # remove a fully masked sample from the Germany training data
        if self.args.nr_classes == 9 and self.args.split == 'train':
            if self.args.input_data_type == 'extracted':
                bad_idx = [1225]
            elif self.args.input_data_type == 'extracted-640':
                bad_idx = [12250, 12251, 12252, 12253, 12254, 12255, 12256,␣
↪12257, 12258, 12259]
            else:
                bad_idx = []
            self.X = np.delete(self.X, bad_idx, axis=0)
            self.mask = np.delete(self.mask, bad_idx, axis=0)
            self.fid = np.delete(self.fid, bad_idx, axis=0)
            self.labels = np.delete(self.labels, bad_idx, axis=0)
```

```
    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        X = self.X[idx]
        label = self.labels[idx]
        mask = self.mask[idx]
        fid = self.fid[idx]
        if self.extra_features is not None:
            extra_f = self.extra_features[idx]
        else: extra_f = np.zeros_like(1)

        return (X, mask, fid, extra_f), label


class PlanetDataset(EarthObservationDataset):
    '''
    Planet Dataset

    If args.ndvi, calculates indices:

    Normalized difference vegetation index (NDVI)

    If args.drop_channels, drop all bands

    '''

    def __init__(self, args):
        super().__init__(args)
        if args.ndvi:
            ndvi = PlanetDataset._calc_ndvi(self.X)
            ndvi = np.expand_dims(ndvi, axis=2) # changed axis from 1 to 2
            if args.drop_channels:
                self.X = ndvi
            else:
                self.X = np.concatenate([self.X, ndvi], axis=2) # changed axis␣
 ↪from 1 to 2

        if args.nr_classes == 9 and args.vegetation_period: # Germany
            ix_train_start = 83 # defined as the minimum of NDVI
            ix_test_start  = 90 # such that NDVI maxima match
            vg_length      = 180 # length of the vegetation period

            if args.split == 'train':
                self.X = self.X[:, ix_train_start:ix_train_start + vg_length]
            elif args.split == 'test':
```

```
                self.X = self.X[:, ix_test_start:ix_test_start + vg_length]

        print('Final shape for Planet image stack', self.X.shape)

        '''
        # normalization of datasets min-max
        xmin=np.min(self.X, axis=(0,1,3))
        xmax=np.max(self.X, axis=(0,1,3))
        for i in range(self.X.shape[2]):
            self.X[:,:,i,:] = (self.X[:,:,i,:] - xmin[i])/(xmax[i] - xmin[i])
        '''

    @staticmethod
    def _calc_ndvi(X):
        '''
        Calculate the normalized vegetation index

        NDVI = (NIR - RED) / (NIR + RED)

        '''
        #print(X.shape) #(4143, 244, 4, 64)
        nir = X[:, :, 3, :] # X[:, 3]
        red = X[:, :, 2, :] # X[:, 2]
        ndvi = (nir - red) / (nir + red)
        ndvi = np.nan_to_num(ndvi)
        return ndvi

class CombinedDataset(Dataset):
    '''
    Class for a combined dataset, holds PlanetDataset, Sentinel1Dataset,␣
 ↪Sentinel2Dataset
    as specified by args.input_data
    '''
    def __init__(self, args):
        super().__init__()
        self.datasets =[]
        self.input_data = args.input_data.copy()
        for input_data in self.input_data:
            if input_data=='planet':
                args.input_data = ['planet']
                planet_dataset = PlanetDataset(args)
                self.datasets.append(planet_dataset)
            elif input_data=='planet-5':
                args.input_data = ['planet-5']
                planet5_dataset = PlanetDataset(args)
                self.datasets.append(planet5_dataset)
```

```
            elif input_data=='sentinel-1':
                args.input_data = ['sentinel-1']
                sentinel1_dataset = Sentinel1Dataset(args)
                self.datasets.append(sentinel1_dataset)
            elif input_data=='sentinel-2':
                args.input_data = ['sentinel-2']
                sentinel2_dataset = Sentinel2Dataset(args)
                self.datasets.append(sentinel2_dataset)
        args.input_data = self.input_data
        for i in range(1, len(self.datasets)):
            print('Assert dataset shape match', i-1, i)
            assert (self.datasets[i-1].fid==self.datasets[i].fid).all(),'s1, s2␣
↪and/or planet not sorted correctly'

    def __len__(self):
        return len(self.datasets[0].labels)

    def __getitem__(self, idx):
        return tuple(d[idx] for d in self.datasets)


class AddGaussianNoise(object):
    '''
    Add Gaussian noise to a sample
    '''
    def __init__(self, mean=0., std=1.):
        self.std = std
        self.mean = mean

    def __call__(self, tensor):
        return tensor + randn(tensor.size()) * self.std + self.mean

    def __repr__(self):
        return self.__class__.__name__ + '(mean={0}, std={1})'.format(self.mean,␣
↪self.std)
```

In the following the model components are listed:

Pixel-Set-Encoder

[3]:
```
class PixelSetEncoder(nn.Module):
    def __init__(self, input_dim, mlp1=[10, 32, 64], pooling='mean_std',␣
↪mlp2=[64, 128],
                 with_extra=True, extra_size=4):
        """
        Pixel-set encoder.
        Args:
            input_dim (int): Number of channels of the input tensors
```

```
            mlp1 (list):  Dimensions of the successive feature spaces of MLP1
            pooling (str): Pixel-embedding pooling strategy, can be chosen in␣
↪('mean','std','max,'min')
                or any underscore-separated combination thereof.
            mlp2 (list): Dimensions of the successive feature spaces of MLP2
            with_extra (bool): Whether additional pre-computed features are␣
↪passed between the two MLPs
            extra_size (int, optional): Number of channels of the additional␣
↪features, if any.
        """
        super(PixelSetEncoder, self).__init__()

        self.input_dim = input_dim
        self.mlp1_dim = copy.deepcopy(mlp1)
        self.mlp2_dim = copy.deepcopy(mlp2)
        self.pooling = pooling

        self.with_extra = with_extra
        self.extra_size = extra_size

        self.name = 'PSE-{}-{}-{}'.format('|'.join(list(map(str, self.
↪mlp1_dim))), pooling,
                                          '|'.join(list(map(str, self.
↪mlp2_dim))))

        self.output_dim = input_dim * len(pooling.split('_')) if len(self.
↪mlp2_dim) == 0 else self.mlp2_dim[-1]

        inter_dim = self.mlp1_dim[-1] * len(pooling.split('_'))


        if self.with_extra:
            self.name += 'Extra'
            inter_dim += self.extra_size

        assert (input_dim == mlp1[0])
        assert (inter_dim == mlp2[0])
        # Feature extraction
        layers = []
        for i in range(len(self.mlp1_dim) - 1):
            layers.append(linlayer(self.mlp1_dim[i], self.mlp1_dim[i + 1]))
        self.mlp1 = nn.Sequential(*layers)

        # MLP after pooling
        layers = []
        for i in range(len(self.mlp2_dim) - 1):
```

```
            layers.append(nn.Linear(self.mlp2_dim[i], self.mlp2_dim[i + 1]))
            layers.append(nn.BatchNorm1d(self.mlp2_dim[i + 1]))
            if i < len(self.mlp2_dim) - 2:
                layers.append(nn.ReLU())
        self.mlp2 = nn.Sequential(*layers)

    def forward(self, input):
        """
        The input of the PSE is a tuple of tensors as yielded by the␣
↪PixelSetData class:
          (Pixel-Set, Pixel-Mask) or ((Pixel-Set, Pixel-Mask), Extra-features)
        Pixel-Set : Batch_size x (Sequence length) x Channel x Number of pixels
        Pixel-Mask : Batch_size x (Sequence length) x Number of pixels
        Extra-features : Batch_size x (Sequence length) x Number of features

        If the input tensors have a temporal dimension, it will be combined with␣
↪the batch dimension so that the
        complete sequences are processed at once. Then the temporal dimension is␣
↪separated back to produce a tensor of
        shape Batch_size x Sequence length x Embedding dimension
        """
        a, b = input
        if len(a) == 2: # extra features included
            out, mask = a
            extra = b
            if len(extra) == 2:
                extra, bm = extra
            extra = extra.unsqueeze(1).repeat(1, out.size(1) ,1).float()
        else:
            out, mask = a, b
        mask = mask.unsqueeze(1).repeat(1, out.size(1) ,1)

        if len(out.shape) == 4:
            # Combine batch and temporal dimensions in case of sequential input
            reshape_needed = True
            batch, temp = out.shape[:2]

            out = out.view(batch * temp, *out.shape[2:])
            mask = mask.view(batch * temp, -1)
            if self.with_extra:
                extra = extra.view(batch * temp, -1)
        else:
            reshape_needed = False
        out = self.mlp1(out)
        out = torch.cat([pooling_methods[n](out, mask) for n in self.pooling.
↪split('_')], dim=1)
```

```
        if self.with_extra:
            out = torch.cat([out, extra], dim=1)
        out = self.mlp2(out)
        if reshape_needed:
            out = out.view(batch, temp, -1)
        return out

class linlayer(nn.Module):
    def __init__(self, in_dim, out_dim):
        super(linlayer, self).__init__()
        self.in_dim = in_dim
        self.out_dim = out_dim

        self.lin = nn.Linear(in_dim, out_dim)
        self.bn = nn.BatchNorm1d(out_dim)

    def forward(self, input):
        out = input.permute((0, 2, 1))  # to channel last
        out = self.lin(out)

        out = out.permute((0, 2, 1))  # to channel first
        out = self.bn(out)
        out = F.relu(out)

        return out

def masked_mean(x, mask):
    out = x.permute((1, 0, 2))
    out = out * mask
    out = out.sum(dim=-1) / mask.sum(dim=-1)
    out = out.permute((1, 0))
    return out

def masked_std(x, mask):
    m = masked_mean(x, mask)

    out = x.permute((2, 0, 1))
    out = out - m
    out = out.permute((2, 1, 0))

    out = out * mask
    d = mask.sum(dim=-1)
    d[d == 1] = 2

    out = (out ** 2).sum(dim=-1) / (d - 1)
    out = torch.sqrt(out + 10e-32) # To ensure differentiability
    out = out.permute(1, 0)
```

```
    return out

def maximum(x, mask):
    return x.max(dim=-1)[0].squeeze()

def minimum(x, mask):
    return x.min(dim=-1)[0].squeeze()

pooling_methods = {
    'mean': masked_mean,
    'std': masked_std,
    'max': maximum,
    'min': minimum
}
```

Lightweight Temporal Attention Encoder Module

[4]:
```
class LTAE(nn.Module):
    def __init__(self, in_channels=128, n_head=16, d_k=8, n_neurons=[256,128],␣
↪dropout=0.2,
                 d_model=256, T=1000, len_max_seq=24, positions=None,␣
↪return_att=False):
        """
        Sequence-to-embedding encoder.
        Args:
            in_channels (int): Number of channels of the input embeddings
            n_head (int): Number of attention heads
            d_k (int): Dimension of the key and query vectors
            n_neurons (list): Defines the dimensions of the successive feature␣
↪spaces of the MLP
                that processes the concatenated outputs of the attention heads
            dropout (float): dropout
            T (int): Period to use for the positional encoding
            len_max_seq (int, optional): Maximum sequence length, used to␣
↪pre-compute the positional
                encoding table
            positions (list, optional): List of temporal positions to use␣
↪instead of position
                in the sequence
            d_model (int, optional): If specified, the input tensors will first␣
↪processed by a
                fully connected layer to project them into a feature space of␣
↪dimension d_model
            return_att (bool): If true, the module returns the attention masks␣
↪along with the
```

```
                embeddings (default False)

        """

        super(LTAE, self).__init__()
        self.in_channels = in_channels
        self.positions = positions
        self.n_neurons = copy.deepcopy(n_neurons)
        self.return_att = return_att

        if positions is None:
            positions = len_max_seq + 1

        if d_model is not None:
            self.d_model = d_model
            self.inconv = nn.Sequential(nn.Conv1d(in_channels, d_model, 1),
                                        nn.LayerNorm((d_model, len_max_seq)))
        else:
            self.d_model = in_channels
            self.inconv = None

        sin_tab = get_sinusoid_encoding_table(positions, self.d_model // n_head,␣
↪T=T)
        self.position_enc = nn.Embedding.from_pretrained(torch.cat([sin_tab for␣
↪_ in range(n_head)], dim=1),
                                                         freeze=True)
        self.inlayernorm = nn.LayerNorm(self.in_channels)
        self.outlayernorm = nn.LayerNorm(n_neurons[-1])
        self.attention_heads = MultiHeadAttention(n_head=n_head, d_k=d_k,␣
↪d_in=self.d_model)

        assert (self.n_neurons[0] == self.d_model)

        activation = nn.ReLU()

        layers = []
        for i in range(len(self.n_neurons) - 1):
            layers.extend([nn.Linear(self.n_neurons[i], self.n_neurons[i + 1]),
                           nn.BatchNorm1d(self.n_neurons[i + 1]),
                           activation])

        self.mlp = nn.Sequential(*layers)
        self.dropout = nn.Dropout(dropout)

    def forward(self, x):

        sz_b, seq_len, d = x.shape
```

```
        x = self.inlayernorm(x)

        if self.inconv is not None:
            x = self.inconv(x.permute(0, 2, 1)).permute(0, 2, 1)

        if self.positions is None:
            src_pos = torch.arange(1, seq_len + 1, dtype=torch.long).
↪expand(sz_b, seq_len).to(x.device)
        else:
            src_pos = torch.arange(0, seq_len, dtype=torch.long).expand(sz_b,␣
↪seq_len).to(x.device)
        enc_output = x + self.position_enc(src_pos)
        enc_output, attn = self.attention_heads(enc_output, enc_output,␣
↪enc_output)
        enc_output = enc_output.permute(1, 0, 2).contiguous().view(sz_b, -1)  #␣
↪Concatenate heads
        enc_output = self.outlayernorm(self.dropout(self.mlp(enc_output)))

        if self.return_att:
            return enc_output, attn
        else:
            return enc_output


class MultiHeadAttention(nn.Module):
    ''' Multi-Head Attention module '''

    def __init__(self, n_head, d_k, d_in):
        super().__init__()
        self.n_head = n_head
        self.d_k = d_k
        self.d_in = d_in

        self.Q = nn.Parameter(torch.zeros((n_head, d_k))).requires_grad_(True)
        nn.init.normal_(self.Q, mean=0, std=np.sqrt(2.0 / (d_k)))

        self.fc1_k = nn.Linear(d_in, n_head * d_k)
        nn.init.normal_(self.fc1_k.weight, mean=0, std=np.sqrt(2.0 / (d_k)))

        self.attention = ScaledDotProductAttention(temperature=np.power(d_k, 0.
↪5))

    def forward(self, q, k, v):
        d_k, d_in, n_head = self.d_k, self.d_in, self.n_head
        sz_b, seq_len, _ = q.size()
```

```
        q = torch.stack([self.Q for _ in range(sz_b)], dim=1).view(-1, d_k)  #␣
↪(n*b) x d_k

        k = self.fc1_k(v).view(sz_b, seq_len, n_head, d_k)
        k = k.permute(2, 0, 1, 3).contiguous().view(-1, seq_len, d_k)  # (n*b) x␣
↪lk x dk

        v = torch.stack(v.split(v.shape[-1] // n_head, dim=-1)).view(n_head *␣
↪sz_b, seq_len, -1)
        output, attn = self.attention(q, k, v)
        attn = attn.view(n_head, sz_b, 1, seq_len)
        attn = attn.squeeze(dim=2)

        output = output.view(n_head, sz_b, 1, d_in // n_head)
        output = output.squeeze(dim=2)

        return output, attn


class ScaledDotProductAttention(nn.Module):
    ''' Scaled Dot-Product Attention '''

    def __init__(self, temperature, attn_dropout=0.1):
        super().__init__()
        self.temperature = temperature
        self.dropout = nn.Dropout(attn_dropout)
        self.softmax = nn.Softmax(dim=2)

    def forward(self, q, k, v):
        attn = torch.matmul(q.unsqueeze(1), k.transpose(1, 2))
        attn = attn / self.temperature

        attn = self.softmax(attn)
        attn = self.dropout(attn)
        output = torch.matmul(attn, v)

        return output, attn


def get_sinusoid_encoding_table(positions, d_hid, T=1000):
    ''' Sinusoid position encoding table
    positions: int or list of integer, if int range(positions)'''

    if isinstance(positions, int):
        positions = list(range(positions))

    def cal_angle(position, hid_idx):
```

```
        return position / np.power(T, 2 * (hid_idx // 2) / d_hid)

    def get_posi_angle_vec(position):
        return [cal_angle(position, hid_j) for hid_j in range(d_hid)]

    sinusoid_table = np.array([get_posi_angle_vec(pos_i) for pos_i in positions])

    sinusoid_table[:, 0::2] = np.sin(sinusoid_table[:, 0::2])  # dim 2i
    sinusoid_table[:, 1::2] = np.cos(sinusoid_table[:, 1::2])  # dim 2i+1

    if torch.cuda.is_available():
        return torch.FloatTensor(sinusoid_table).cuda()
    else:
        return torch.FloatTensor(sinusoid_table)

def get_sinusoid_encoding_table_var(positions, d_hid, clip=4, offset=3, T=1000):
    ''' Sinusoid position encoding table
    positions: int or list of integer, if int range(positions)'''

    if isinstance(positions, int):
        positions = list(range(positions))

    x = np.array(positions)

    def cal_angle(position, hid_idx):
        return position / np.power(T, 2 * (hid_idx + offset // 2) / d_hid)

    def get_posi_angle_vec(position):
        return [cal_angle(position, hid_j) for hid_j in range(d_hid)]

    sinusoid_table = np.array([get_posi_angle_vec(pos_i) for pos_i in positions])

    sinusoid_table = np.sin(sinusoid_table)  # dim 2i
    sinusoid_table[:, clip:] = torch.zeros(sinusoid_table[:, clip:].shape)

    if torch.cuda.is_available():
        return torch.FloatTensor(sinusoid_table).cuda()
    else:
        return torch.FloatTensor(sinusoid_table)
```

Decoder

[5]:
```
def get_decoder(n_neurons):
    """Returns an MLP with the layer widths specified in n_neurons.
    Every linear layer but the last one is followed by BatchNorm + ReLu

    args:
```

```
        n_neurons (list): List of int that specifies the width and length of the␣
↪MLP.
    """
    layers = []
    for i in range(len(n_neurons)-1):
        layers.append(nn.Linear(n_neurons[i], n_neurons[i+1]))
        if i < (len(n_neurons) - 2):
            layers.extend([
                nn.BatchNorm1d(n_neurons[i + 1]),
                nn.ReLU()
            ])
    m = nn.Sequential(*layers)
    return m
```

The final Model Since we use a single dataset (Planet), we use a single PseLTae model

[6]:
```
class PseLTae(nn.Module):
    """
    Pixel-Set encoder + Lightweight Temporal Attention Encoder sequence␣
↪classifier
    """

    def __init__(self, input_dim=10, mlp1=[10, 32, 64], pooling='mean_std',␣
↪mlp2=[132, 128], with_extra=True,
                 extra_size=4,
                 n_head=16, d_k=8, d_model=256, mlp3=[256, 128], dropout=0.2,␣
↪T=1000, len_max_seq=24, positions=None,
                 mlp4=[128, 64, 32, 20], return_att=False):
        super(PseLTae, self).__init__()
        self.spatial_encoder = PixelSetEncoder(input_dim, mlp1=mlp1,␣
↪pooling=pooling, mlp2=mlp2, with_extra=with_extra,
                                               extra_size=extra_size)
        self.temporal_encoder = LTAE(in_channels=mlp2[-1], n_head=n_head,␣
↪d_k=d_k,
                                     d_model=d_model, n_neurons=mlp3,␣
↪dropout=dropout,
                                     T=T, len_max_seq=len_max_seq,␣
↪positions=positions, return_att=return_att
                                     )
        self.decoder = get_decoder(mlp4)
        self.return_att = return_att
        self.param_ratio()

    def forward(self, input):
        """
         Args:
```

```
            input(tuple): (Pixel-Set, Pixel-Mask) or ((Pixel-Set, Pixel-Mask),␣
↪Extra-features)
            Pixel-Set : Batch_size x Sequence length x Channel x Number of pixels
            Pixel-Mask : Batch_size x Sequence length x Number of pixels
            Extra-features : Batch_size x Sequence length x Number of features
        """
        out = self.spatial_encoder(input) # out size is 8,48,128

        if self.return_att:
            out, att = self.temporal_encoder(out)
            out = self.decoder(out)
            return out, att
        else:
            out = self.temporal_encoder(out)
            out = self.decoder(out)
            return out

    def param_ratio(self):
        total = get_ntrainparams(self)
        s = get_ntrainparams(self.spatial_encoder)
        t = get_ntrainparams(self.temporal_encoder)
        c = get_ntrainparams(self.decoder)

        print('TOTAL TRAINABLE PARAMETERS : {}'.format(total))
        print('RATIOS: Spatial {:5.1f}% , Temporal {:5.1f}% , Classifier {:5.
↪1f}%'.format(s / total * 100,
                                                                            ␣
↪           t / total * 100,
                                                                            ␣
↪           c / total * 100))

        return total
```

1.4.1 Hyperparameters

The hyperparameter optimization was included by us using NNI (https://nni.readthedocs.io/en/stable/). As the model capacity is quite high with the default settings (600k parameters), we deliberately restricted the capacity to counter overfitting. The best results were achieved with a model of about 60k parameters capacity:

- General parameters
  - batch_size: 8
  - with_extra: False (i.e., do not include crop_area and crop_len)
  - augmentation: False (no Gaussian random noise during training)
  - k-folds: 5
- Pixel-Set Encoder module
  - mlp1-in: 16, mlp1-out: 32 (Dimensions of the successive feature spaces of MLP1, Planet)

  - factor: 8 (Scale for MLP3 input dimension)
  - mlp3-out: 64 (MLP3 output dimension, Planet)
- Temporal attention module
  - n-head: 16 (attention heads)
  - d-k: 8 (in temporal attention module)
  - dropout: 0.25
- Decoder module
  - mlp4-1: 32, mlp4-2: 16 (Dimensions of the successive feature spaces of MLP4)

1.4.2 Training Details

The given dataset for training and validation was augmented as described in the preprocessing step, creating 10 samples out of each image. These samples were then randomly divided in training and validation set, however keeping (augmented) samples from the the same field in either the training or validation set, in order to prevent data leakage. In total 80% of the data was used for training and 20% was kept for validation in each fold of the cross-validation.

The training includes the monitoring of several metrics, which are calculated in `./ai4food/evaluation_utils.py`.

As loss fuction, `focal loss` is used, which is not exactly equal to the evaluation metric the model is finally evaluated on, but is close enough for efficient training and is also used in Garnot. et al. (2020). The script is also copied to the Dockerimage. Class weights correspond to the inverse frequencies of the sample counts.

[7]:
```
"""
Credits to  github.com/clcarwin/focal_loss_pytorch
"""

import torch
import torch.nn.functional as F
from torch.autograd import Variable
import torch.nn as nn

class FocalLoss(nn.Module):
    def __init__(self, gamma=0, alpha=None, size_average=True):
        super(FocalLoss, self).__init__()
        self.gamma = gamma
        self.alpha = alpha
        if isinstance(alpha, (float, int)): self.alpha = torch.Tensor([alpha, 1␣
 ↪- alpha])
        if isinstance(alpha, list): self.alpha = torch.Tensor(alpha)
        self.size_average = size_average

    def forward(self, input, target):
        if input.dim() > 2:
            input = input.view(input.size(0), input.size(1), -1)  # N,C,H,W =>␣
 ↪N,C,H*W
```

```
            input = input.transpose(1, 2)  # N,C,H*W => N,H*W,C
            input = input.contiguous().view(-1, input.size(2))  # N,H*W,C =>␣
↪N*H*W,C
        target = target.view(-1, 1)

        logpt = F.log_softmax(input, dim=1)
        logpt = logpt.gather(1, target)
        logpt = logpt.view(-1)
        pt = Variable(logpt.data.exp())

        if self.alpha is not None:
            if self.alpha.type() != input.data.type():
                self.alpha = self.alpha.type_as(input.data)
            at = self.alpha.gather(0, target.data.view(-1))
            logpt = logpt * Variable(at)

        loss = -1 * (1 - pt) ** self.gamma * logpt
        if self.size_average:
            return loss.mean()
        else:
            return loss.sum()
```

For the loss computation, we set `alpha` as the inverse of the class frequencies in the training data, which were found during the exploration phase. In this way we aim to balance the class distribution.

The training routing can be found in `./ai4food/training.py`. To reproduce our model training, execute

```
python training.py --k-fold 5 --num-workers 0 --nr-classes 9 --input-data planet
--input-data-type extracted-640 --target-dir \$scriptdir --split train --gamma 0
--alpha 1 --ndvi 1 --drop-channels 0 --input-dim 5 --max-epochs 100 --save-preds
--save-ref --dev-data-dir /work/ka1176/shared_data/2021-ai4food/dev_data/germany"
--mlp1-in 16 --mlp1-out 32 --mlp3-out 64 --mlp4-1 32 --mlp4-2 16 --factor 8
--n-head 8 --dropout 0.25
```

Each model of the 10-fold cross validation, may be trained for a maximum of 100 epochs, but early stopping is applied, which stops the training routine after 10 epochs if no improvement to the validation accuracy is observed. Then the best performing model in terms of validation accuracy is saved.

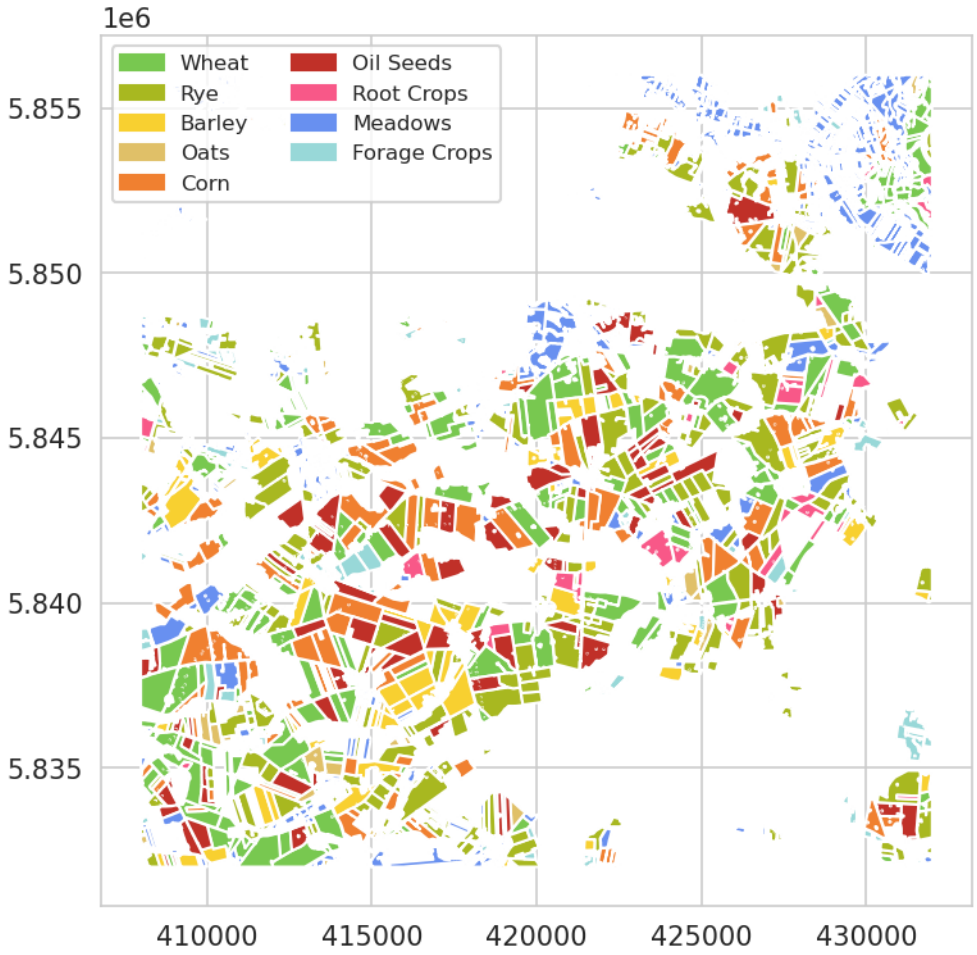
To run inference with the trained models on the test set and generate a submission file, execute

```
python training.py --k-fold 5 --num-workers 0 --nr-classes 9 --input-data
planet --input-data-type extracted-640 --target-dir \$scriptdir --split
test --majority 1 --gamma 0 --alpha 1 --ndvi 1 --drop-channels 0
--input-dim 5 --max-epochs 100 --save-preds --save-ref --dev-data-dir
/work/ka1176/shared_data/2021-ai4food/dev_data/germany" --mlp1-in 16 --mlp1-out
32 --mlp3-out 64 --mlp4-1 32 --mlp4-2 16 --factor 8 --n-head 8 --dropout 0.25
```

During inference all 5 models of the cross validation are used and an average of the probabilities of each model is obtained to get the final prediction for each sample.

1.5 Results

Crop fields colored with the predicted crop ID, as obtained from our best submission with a score of 4.42



[ ]: