Image Analysis

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Chapter 1

Namespace Index

1.1 Packages

Here are the packages with brief descriptions (if available):

Chapter 2

Hierarchical Index

2.1 Class Hierarchy

This inheritance list is sorted roughly, but not completely, alphabetically:

Chapter 3

Class Index

3.1 Class List

Here are the classes, structs, unions and interfaces with brief descriptions:

Chapter 4

File Index

4.1 File List

Here is a list of all files with brief descriptions:

Chapter 5

Namespace Documentation

5.1 imagetools Namespace Reference

Namespaces

- ml
- plotting
- signals

5.2 imagetools.ml Namespace Reference

Classes

- class KMeans_Custom

  Implements a class that handles KMeans Clustering.

Functions

- def gradient_descent (obj, grad, x0, obj_min, eps, lr, max_iters, filename)

  Implements vanilla gradient descent for scalar functions on R2.

5.2.1 Function Documentation

5.2.1.1 gradient_descent()

```
def imagetools.ml.gradient_descent (
              obj,
              grad,
              x0,
              obj_min,
              eps,
              lr,
              max_iters,
              filename )
```

Implements vanilla gradient descent for scalar functions on R2.

```
    @param obj The objective function to minimise.
    @param grad The gradient of the objective function (R^2-->R^2)
    @param x0 The initial iterate
    @param obj_min The minimal value of the objective function
    @param eps The threshold error for the stopping criterion
    @param lr The learning rate
    @param max_iters The maximum number of iterations to run before
    terminating
    @param filename Determines the name of the trajectory and loss plot
    file
    @return x estimated argmin (in R^2) of the objective
```

5.3 imagetools.plotting Namespace Reference

Functions

- def plot_image (ax_sp, img, title, cmap, gt=None)

5.3.1 Function Documentation

5.3.1.1 plot_image()

```
def imagetools.plotting.plot_image (
              ax_sp,
              img,
              title,
              cmap,
              gt = None )
```

5.4 imagetools.signals Namespace Reference

Functions

- def iterative_soft_thresholding (data_sampled, lam, n_iters, gt=None)

    Implements ISTA in 1D.
- def fft1c (x)
- def ifft1c (y)
- def ComplexSoftThresh (y, lam)
- def coeffs2img (LL, coeffs)
- def img2coeffs (Wim, levels=4)
- def unstack_coeffs (Wim)
- def dwt2 (im)
- def idwt2 (Wim)

5.4.1 Function Documentation

5.4.1.1 coeffs2img()

```
def imagetools.signals.coeffs2img (
              LL,
              coeffs )
```

5.4.1.2 ComplexSoftThresh()

```
def imagetools.signals.ComplexSoftThresh (
              y,
              lam )
```

5.4.1.3 dwt2()

```
def imagetools.signals.dwt2 (
              im )
```

5.4.1.4 fft1c()

```
def imagetools.signals.fft1c (
              x )
```

5.4.1.5 idwt2()

```
def imagetools.signals.idwt2 (
             Wim )
```

5.4.1.6 ifft1c()

```
def imagetools.signals.ifft1c (
             y )
```

5.4.1.7 img2coeffs()

```
def imagetools.signals.img2coeffs (
             Wim,
             levels = 4 )
```

5.4.1.8 iterative_soft_thresholding()

```
def imagetools.signals.iterative_soft_thresholding (
             data_sampled,
             lam,
             n_iters,
             gt = None )
```

Implements ISTA in 1D.

```
    @param data_sampled The subsampled measurement vector
    @param lam The soft-thresholding (regularisation) parameter
    @param n_iters Number of iterations
    @param gt Ground truth measurements to compare to
    @return predictions (N, P) array of centroids
```

5.4.1.9 unstack_coeffs()

```
def imagetools.signals.unstack_coeffs (
             Wim )
```

5.5 inverse_problems Namespace Reference

Variables

- file_list = f.read().split("\n")[:-1]
- y_noisy = np.array([float(x) for x in file_list])
- y_outlier = np.array([float(x) for x in file_list])
- x = np.arange(len(y_noisy))
- a_noisy_l2 = np.sum(x ∗ y_noisy) / np.sum(x ∗ x)
- b_noisy_l2 = np.mean(y_noisy) - a_noisy_l2 ∗ np.mean(x)
- a_outlier_l2 = np.sum(x ∗ y_outlier) / np.sum(x ∗ x)
- b_outlier_l2 = np.mean(y_outlier) - a_outlier_l2 ∗ np.mean(x)
- fig
- ax
- figsize
- list B_coefs = [ ]
- obj_l1 = lambda B: np.sum(np.abs(B[0] ∗ x + B[1] - y))
- grad_l1
- B0 = np.array([0.1, 0.1])
- float lr = 0.0001
- B = gradient_descent(obj_l1, grad_l1, B0, 0, 0.01, lr, 100, "gd_l1")
- rng = np.random.default_rng(seed=42)
- signal = np.zeros(100)
- data = fft1c(signal)
- int sample_freq = 4
- mask_random = rng.uniform(0, 1, 100)
- mask_unif = np.zeros(100)
- start_index = rng.integers(0, sample_freq)
- sample_random = mask_random ∗ data
- sample_unif = mask_unif ∗ data
- int signal_random = ifft1c(sample_random) ∗ sample_freq
- int signal_unif = ifft1c(sample_unif) ∗ sample_freq
- data_random_recon
- mse_random
- lam
- n_iters = 1000
- gt
- data_unif_recon
- mse_unif
- int signal_random_recon = ifft1c(data_random_recon) ∗ sample_freq
- int signal_unif_recon = ifft1c(data_unif_recon) ∗ sample_freq
- label
- title
- xlabel
- ylabel
- river_img = skimage.io.imread("data/river_side.jpeg")
- river_img_dw = dwt2(river_img)
- river_img_recon = idwt2(river_img_dw)
- th = np.quantile(abs(river_img_dw), 0.85)
- river_img_dw_th = abs(river_img_dw) > th
- tuple plotrange
- aximg0 = ax[0].imshow(abs(river_img_dw), vmin=plotrange[0], vmax=plotrange[1])
- aximg1 = ax[1].imshow(abs(river_img_dw_th), cmap="grey")
- float obj = lambda x: 0.5 ∗ (x[0] ∗∗ 2) + (x[1] ∗∗ 2)
- grad = lambda x: np.array([x[0], 2.0 ∗ x[1]])
- x0 = np.array([1.0, 1.0])
- float eps = 0.01
- float obj_min = 0.0

5.5.1 Variable Documentation

5.5.1.1 a_noisy_l2

```
inverse_problems.a_noisy_l2 = np.sum(x * y_noisy) / np.sum(x * x)
```

5.5.1.2 a_outlier_l2

```
inverse_problems.a_outlier_l2 = np.sum(x * y_outlier) / np.sum(x * x)
```

5.5.1.3 ax

```
inverse_problems.ax
```

5.5.1.4 aximg0

```
inverse_problems.aximg0 = ax[0].imshow(abs(river_img_dw), vmin=plotrange[0], vmax=plotrange[1])
```

5.5.1.5 aximg1

```
inverse_problems.aximg1 = ax[1].imshow(abs(river_img_dw_th), cmap="grey")
```

5.5.1.6 B

```
inverse_problems.B = gradient_descent(obj_l1, grad_l1, B0, 0, 0.01, lr, 100, "gd_l1")
```

5.5.1.7 B0

```
inverse_problems.B0 = np.array([0.1, 0.1])
```

5.5.1.8 B_coefs

```
list inverse_problems.B_coefs = [ ]
```

5.5.1.9 b_noisy_l2

```
inverse_problems.b_noisy_l2 = np.mean(y_noisy) - a_noisy_l2 * np.mean(x)
```

5.5.1.10 b_outlier_l2

```
inverse_problems.b_outlier_l2 = np.mean(y_outlier) - a_outlier_l2 * np.mean(x)
```

5.5.1.11 data

```
inverse_problems.data = fft1c(signal)
```

5.5.1.12 data_random_recon

```
inverse_problems.data_random_recon
```

5.5.1.13 data_unif_recon

```
inverse_problems.data_unif_recon
```

5.5.1.14 eps

```
float inverse_problems.eps = 0.01
```

5.5.1.15 fig

```
inverse_problems.fig
```

5.5.1.16 figsize

```
inverse_problems.figsize
```

5.5.1.17 file_list

```
inverse_problems.file_list = f.read().split("\n")[:-1]
```

5.5.1.18 grad

```
inverse_problems.grad = lambda x:  np.array([x[0], 2.0 * x[1]])
```

5.5.1.19 grad_l1

```
inverse_problems.grad_l1
```

Initial value:

```
=  lambda B: np.array(
        [
            np.dot(x, np.sign(B[0] * x + B[1] - y)),
            np.sum(np.sign(B[0] * x + B[1] - y)),
        ]
    )
```

5.5.1.20 gt

```
inverse_problems.gt
```

5.5.1.21 label

```
inverse_problems.label
```

5.5.1.22 lam

```
inverse_problems.lam
```

5.5.1.23 lr

```
float inverse_problems.lr = 0.0001
```

5.5.1.24 mask_random

```
inverse_problems.mask_random = rng.uniform(0, 1, 100)
```

5.5.1.25 mask_unif

```
inverse_problems.mask_unif = np.zeros(100)
```

5.5.1.26 mse_random

```
inverse_problems.mse_random
```

5.5.1.27 mse_unif

```
inverse_problems.mse_unif
```

5.5.1.28 n_iters

```
int inverse_problems.n_iters = 1000
```

5.5.1.29 obj

```
float inverse_problems.obj = lambda x:  0.5 * (x[0] ** 2) + (x[1] ** 2)
```

5.5.1.30 obj_l1

```
inverse_problems.obj_l1 = lambda B: np.sum(np.abs(B[0] * x + B[1] - y))
```

5.5.1.31 obj_min

```
float inverse_problems.obj_min = 0.0
```

5.5.1.32 plotrange

```
tuple inverse_problems.plotrange
```

Initial value:

```
=  (
    np.quantile(abs(river_img_dw), 0.005),
    np.quantile(abs(river_img_dw), 0.995),
)
```

5.5.1.33 river_img

```
inverse_problems.river_img = skimage.io.imread("data/river_side.jpeg")
```

5.5.1.34 river_img_dw

```
inverse_problems.river_img_dw = dwt2(river_img)
```

5.5.1.35 river_img_dw_th

```
inverse_problems.river_img_dw_th = abs(river_img_dw) > th
```

5.5.1.36 river_img_recon

```
inverse_problems.river_img_recon = idwt2(river_img_dw)
```

5.5.1.37 rng

```
inverse_problems.rng = np.random.default_rng(seed=42)
```

5.5.1.38 sample_freq

```
int inverse_problems.sample_freq = 4
```

5.5.1.39 sample_random

```
inverse_problems.sample_random = mask_random * data
```

5.5.1.40 sample_unif

```
inverse_problems.sample_unif = mask_unif * data
```

5.5.1.41 signal

```
inverse_problems.signal = np.zeros(100)
```

5.5.1.42 signal_random

```
int inverse_problems.signal_random = ifft1c(sample_random) * sample_freq
```

5.5.1.43 signal_random_recon

```
int inverse_problems.signal_random_recon = ifft1c(data_random_recon) * sample_freq
```

5.5.1.44 signal_unif

```
int inverse_problems.signal_unif = ifft1c(sample_unif) * sample_freq
```

5.5.1.45 signal_unif_recon

```
int inverse_problems.signal_unif_recon = ifft1c(data_unif_recon) * sample_freq
```

5.5.1.46 start_index

```
inverse_problems.start_index = rng.integers(0, sample_freq)
```

5.5.1.47 th

```
inverse_problems.th = np.quantile(abs(river_img_dw), 0.85)
```

5.5.1.48 title

```
inverse_problems.title
```

5.5.1.49 x

```
inverse_problems.x = np.arange(len(y_noisy))
```

5.5.1.50 x0

```
inverse_problems.x0 = np.array([1.0, 1.0])
```

5.5.1.51 xlabel

```
inverse_problems.xlabel
```

5.5.1.52 y_noisy

```
inverse_problems.y_noisy = np.array([float(x) for x in file_list])
```

5.5.1.53 y_outlier

```
inverse_problems.y_outlier = np.array([float(x) for x in file_list])
```

5.5.1.54 ylabel

```
inverse_problems.ylabel
```

5.6 lgd Namespace Reference

Classes

- class prox_net
- class LGD_net

Variables

- parser = argparse.ArgumentParser()
- type
- str
- choices
- required
- args = parser.parse_args()
- int img_size = 256
- reco_space
- int num_angles = 30
- geometry = odl.tomo.parallel_beam_geometry(reco_space, num_angles=num_angles)
- fwd_op_odl = odl.tomo.RayTransform(reco_space, geometry)
- fbp_op_odl
- adj_op_odl = fwd_op_odl.adjoint
- phantom_odl = odl.phantom.shepp_logan(reco_space, modified=True)
- data_odl = fwd_op_odl(phantom_odl)
- fbp_odl = fbp_op_odl(data_odl)
- phantom_np = phantom_odl.__array__()
- fbp_np = fbp_odl.__array__()
- data_np = data_odl.__array__()
- fig
- ax
- figsize
- gt
- grad = odl.Gradient(reco_space)
- L = odl.BroadcastOperator(fwd_op_odl, grad)
- data_fit = odl.solvers.L2NormSquared(fwd_op_odl.range).translated(data_odl)
- float lam = 0.015
- float reg_func = lam ∗ odl.solvers.L1Norm(grad.range)
- g = odl.solvers.SeparableSum(data_fit, reg_func)
- f = odl.solvers.ZeroFunctional(L.domain)
- float op_norm = 1.1 ∗ odl.power_method_opnorm(L, maxiter=20)
- int niter = 200
- float sigma = 2.0
- float tau = sigma / op_norm∗∗2
- callback
- x_admm_odl = L.domain.zero()
- x_admm_np = x_admm_odl.__array__()
- tuple device

- int step_size = 1 / op_norm
- lgd_net = LGD_net().to(device)
- num_learnable_params
- tuple y
- tuple x_init
- tuple ground_truth
- mse_loss = torch.nn.MSELoss()
- optimizer = torch.optim.Adam(lgd_net.parameters(), lr=1e-4)
- int num_epochs = 2000
- ckpt = torch.load("outputs/weights_1990.pth", map_location=device)
- int start_idx = 1989
- losses = ckpt["losses"]
- int save_interval = 1
- int verbose_interval = 1
- recon = lgd_net(y, x_init)
- loss = mse_loss(recon, ground_truth)
- dictionary checkpoint
- string checkpoint_filepath = f"outputs/weights_{epoch+1:03d}.pth"
- tuple lgd_recon_np

5.6.1 Variable Documentation

5.6.1.1 adj_op_odl

```
lgd.adj_op_odl = fwd_op_odl.adjoint
```

5.6.1.2 args

```
lgd.args = parser.parse_args()
```

5.6.1.3 ax

```
lgd.ax
```

5.6.1.4 callback

```
lgd.callback
```

Initial value:

```
=  odl.solvers.CallbackPrintIteration(
    step=10
) & odl.solvers.CallbackShow(step=10)
```

5.6.1.5 checkpoint

```
dictionary lgd.checkpoint
```

Initial value:

```
=  {
            "epoch":  epoch + 1,
            "state_dict":  lgd_net.state_dict(),
            "optimizer":  optimizer.state_dict(),
            "losses":  losses,
        }
```

5.6.1.6 checkpoint_filepath

```
string lgd.checkpoint_filepath = f"outputs/weights_{epoch+1:03d}.pth"
```

5.6.1.7 choices

```
lgd.choices
```

5.6.1.8 ckpt

```
lgd.ckpt = torch.load("outputs/weights_1990.pth", map_location=device)
```

5.6.1.9 data_fit

```
lgd.data_fit = odl.solvers.L2NormSquared(fwd_op_odl.range).translated(data_odl)
```

5.6.1.10 data_np

```
lgd.data_np = data_odl.__array__()
```

5.6.1.11 data_odl

```
lgd.data_odl = fwd_op_odl(phantom_odl)
```

5.6.1.12 device

```
tuple lgd.device
```

Initial value:

```
=  (
    torch.device("cuda") if torch.cuda.is_available() else torch.device("cpu")
)
```

5.6.1.13 f

```
lgd.f = odl.solvers.ZeroFunctional(L.domain)
```

5.6.1.14 fbp_np

```
lgd.fbp_np = fbp_odl.__array__()
```

5.6.1.15 fbp_odl

```
lgd.fbp_odl = fbp_op_odl(data_odl)
```

5.6.1.16 fbp_op_odl

```
lgd.fbp_op_odl
```

Initial value:

```
=  odl.tomo.fbp_op(
    fwd_op_odl, filter_type="Ram-Lak", frequency_scaling=0.6
)
```

5.6.1.17 fig

```
lgd.fig
```

5.6.1.18 figsize

```
lgd.figsize
```

5.6.1.19 fwd_op_odl

```
lgd.fwd_op_odl = odl.tomo.RayTransform(reco_space, geometry)
```

5.6.1.20 g

```
lgd.g = odl.solvers.SeparableSum(data_fit, reg_func)
```

5.6.1.21 geometry

```
lgd.geometry = odl.tomo.parallel_beam_geometry(reco_space, num_angles=num_angles)
```

5.6.1.22 grad

```
lgd.grad = odl.Gradient(reco_space)
```

5.6.1.23 ground_truth

```
tuple lgd.ground_truth
```

Initial value:

```
= (
    torch.from_numpy(phantom_np).to(device).unsqueeze(0)
)
```

5.6.1.24 gt

```
lgd.gt
```

5.6.1.25 img_size

```
int lgd.img_size = 256
```

5.6.1.26 L

```
lgd.L = odl.BroadcastOperator(fwd_op_odl, grad)
```

5.6.1.27 lam

```
float lgd.lam = 0.015
```

5.6.1.28 lgd_net

```
lgd.lgd_net = LGD_net().to(device)
```

5.6.1.29 lgd_recon_np

```
tuple lgd.lgd_recon_np
```

Initial value:

```
=  (
    recon.detach().cpu().numpy().squeeze()
)
```

5.6.1.30 loss

```
lgd.loss = mse_loss(recon, ground_truth)
```

5.6.1.31 losses

```
list lgd.losses = ckpt["losses"]
```

5.6.1.32 mse_loss

```
lgd.mse_loss = torch.nn.MSELoss()
```

5.6.1.33 niter

```
lgd.niter = 200
```

5.6.1.34 num_angles

```
int lgd.num_angles = 30
```

5.6.1.35 num_epochs

```
int lgd.num_epochs = 2000
```

5.6.1.36 num_learnable_params

```
lgd.num_learnable_params
```

Initial value:

```
=  sum(
    p.numel() for p in lgd_net.parameters() if p.requires_grad
)
```

5.6.1.37 op_norm

```
float lgd.op_norm = 1.1 * odl.power_method_opnorm(L, maxiter=20)
```

5.6.1.38 optimizer

```
lgd.optimizer = torch.optim.Adam(lgd_net.parameters(), lr=1e-4)
```

5.6.1.39 parser

```
lgd.parser = argparse.ArgumentParser()
```

5.6.1.40 phantom_np

```
lgd.phantom_np = phantom_odl.__array__()
```

5.6.1.41 phantom_odl

```
lgd.phantom_odl = odl.phantom.shepp_logan(reco_space, modified=True)
```

5.6.1.42 reco_space

```
lgd.reco_space
```

Initial value:

```
=  odl.uniform_discr(
    min_pt=[-20, -20],
    max_pt=[20, 20],
    shape=[img_size, img_size],
    dtype="float32",
)
```

5.6.1.43 recon

```
lgd.recon = lgd_net(y, x_init)
```

5.6.1.44 reg_func

```
float lgd.reg_func = lam * odl.solvers.L1Norm(grad.range)
```

5.6.1.45 required

```
lgd.required
```

5.6.1.46 save_interval

```
int lgd.save_interval = 1
```

5.6.1.47 sigma

```
lgd.sigma = 2.0
```

5.6.1.48 start_idx

```
int lgd.start_idx = 1989
```

5.6.1.49 step_size

```
int lgd.step_size = 1 / op_norm
```

5.6.1.50 str

```
lgd.str
```

5.6.1.51 tau

```
lgd.tau = sigma / op_norm**2
```

5.6.1.52 type

```
lgd.type
```

5.6.1.53 verbose_interval

```
int lgd.verbose_interval = 1
```

5.6.1.54 x_admm_np

```
lgd.x_admm_np = x_admm_odl.__array__()
```

5.6.1.55 x_admm_odl

```
lgd.x_admm_odl = L.domain.zero()
```

5.6.1.56 x_init

```
tuple lgd.x_init
```

Initial value:

```
=  (
    torch.from_numpy(
        fbp_op_odl(y.detach().cpu().numpy().squeeze()).__array__()
    )
    .to(device)
    .unsqueeze(0)
)
```

5.6.1.57 y

```
tuple lgd.y
```

Initial value:

```
=  (
    torch.from_numpy(data_np).to(device).unsqueeze(0)
)
```

5.7 segment Namespace Reference

Variables

- fig
- ax
- figsize
- ct_img = skimage.io.imread("data/CT.png")
- ct_threshold = threshold_otsu(ct_img)
- ct_segmented = ct_img > ct_threshold
- se = disk(4)
- ct_mask = remove_small_objects(binary_opening(ct_segmented, se))
- ct_labelled = label(ct_mask == 0)
- ct_props = regionprops(ct_labelled)
- lung_idx = sorted(list(range(3)), key=lambda i: ct_props[i].area)[:2]
- cmap
- coins_img = skimage.io.imread("data/coins.png")
- coins_marked = coins_img.copy()
- coins_pre = rank.median(coins_img, np.ones((1, 7)))
- int coins_segmented = 1 - chan_vese(coins_pre, mu=0.1)
- coins_labelled = label(coins_segmented)
- list desired_coins_idx
- flowers_img = skimage.io.imread("data/noisy_flower.jpg")
- flowers_pre = denoise_tv_bregman(flowers_img, weight=0.5)
- km = KMeans_Custom(K=6)
- flowers_data = flowers_pre[::8, ::8, :].reshape(-1, 3)
- verbose
- flowers_flat = flowers_pre.reshape(-1, 3)
- flowers_segmented = km.predict_cluster(flowers_flat)
- int flowers_purple = 0

5.7.1 Variable Documentation

5.7.1.1 ax

```
segment.ax
```

5.7.1.2 cmap

```
segment.cmap
```

5.7.1.3 coins_img

```
tuple segment.coins_img = skimage.io.imread("data/coins.png")
```

5.7.1.4 coins_labelled

```
segment.coins_labelled = label(coins_segmented)
```

5.7.1.5 coins_marked

```
segment.coins_marked = coins_img.copy()
```

5.7.1.6 coins_pre

```
segment.coins_pre = rank.median(coins_img, np.ones((1, 7)))
```

5.7.1.7 coins_segmented

```
segment.coins_segmented = 1 - chan_vese(coins_pre, mu=0.1)
```

5.7.1.8 ct_img

```
segment.ct_img = skimage.io.imread("data/CT.png")
```

5.7.1.9 ct_labelled

```
float segment.ct_labelled = label(ct_mask == 0)
```

5.7.1.10 ct_mask

```
segment.ct_mask = remove_small_objects(binary_opening(ct_segmented, se))
```

5.7.1.11 ct_props

```
segment.ct_props = regionprops(ct_labelled)
```

5.7.1.12 ct_segmented

```
segment.ct_segmented = ct_img > ct_threshold
```

5.7.1.13 ct_threshold

```
segment.ct_threshold = threshold_otsu(ct_img)
```

5.7.1.14 desired_coins_idx

```
list segment.desired_coins_idx
```

Initial value:

```
=  [
    coins_labelled[50, 40],
    coins_labelled[125, 100],
    coins_labelled[200, 160],
    coins_labelled[275, 240],
]
```

5.7.1.15 fig

```
segment.fig
```

5.7.1.16 figsize

```
segment.figsize
```

5.7.1.17 flowers_data

```
segment.flowers_data = flowers_pre[::8, ::8, :].reshape(-1, 3)
```

5.7.1.18 flowers_flat

```
segment.flowers_flat = flowers_pre.reshape(-1, 3)
```

5.7.1.19 flowers_img

```
segment.flowers_img = skimage.io.imread("data/noisy_flower.jpg")
```

5.7.1.20 flowers_pre

```
segment.flowers_pre = denoise_tv_bregman(flowers_img, weight=0.5)
```

5.7.1.21 flowers_purple

```
segment.flowers_purple = 0
```

5.7.1.22 flowers_segmented

```
segment.flowers_segmented = km.predict_cluster(flowers_flat)
```

5.7.1.23 km

```
segment.km = KMeans_Custom(K=6)
```

5.7.1.24 lung_idx

```
segment.lung_idx = sorted(list(range(3)), key=lambda i:  ct_props[i].area)[:2]
```

5.7.1.25 se

```
segment.se = disk(4)
```

5.7.1.26 verbose

```
segment.verbose
```

Chapter 6

Class Documentation

6.1 imagetools.ml.KMeans_Custom Class Reference

Implements a class that handles KMeans Clustering.

Public Member Functions

- def __init__ (self, K)
- def assignment (self, data)

  Assigns a matrix where each row represents the assigned centroid.
- def fit (self, data, verbose=10, limit=1e5)

  Fits the KMeans clusters.
- def predict (self, data)

  Returns an array whose rows are the closest centroid to each datum.
- def predict_cluster (self, data)

  Returns an array whose entries are the closest centroid to each datum, mapped to a single identifying integer.

Public Attributes

- K
- centroids

6.1.1 Detailed Description

Implements a class that handles KMeans Clustering.

6.1.2 Constructor & Destructor Documentation

6.1.2.1 __init__()

```
def imagetools.ml.KMeans_Custom.__init__ (
            self,
            K )
```

6.1.3 Member Function Documentation

6.1.3.1 assignment()

```
def imagetools.ml.KMeans_Custom.assignment (
            self,
            data )
```

Assigns a matrix where each row represents the assigned centroid.

Parameters

data	The data to assign labels to. Must be an (N, P) array.

Returns

labels

6.1.3.2 fit()

```
def imagetools.ml.KMeans_Custom.fit (
            self,
            data,
            verbose = 10,
            limit = 1e5 )
```

Fits the KMeans clusters.

```
@details Uses the KMeans++ algorithm to initialise centroids,
and then iteratively updates them using Lloyd's algorithm.

@param data The data to assign labels to. Must be an (N, P) array.
@param verbose How often to print out number of reassigned labels.
@param limit Maximum number of iterations before stopping. Prevents
an indefinite loop.
```

6.1.3.3 predict()

```
def imagetools.ml.KMeans_Custom.predict (
            self,
            data )
```

Returns an array whose rows are the closest centroid to each datum.

Parameters

data	The data to assign labels to. Must be an (N, P) array.

Returns

predictions (N, P) array of centroids

6.1.3.4 predict_cluster()

```
def imagetools.ml.KMeans_Custom.predict_cluster (
              self,
              data )
```

Returns an array whose entries are the closest centroid to each datum, mapped to a single identifying integer.

Parameters

data	The data to assign labels to. Must be an (N, P) array.

Returns

predictions (N, 1) array of predicted clusters

6.1.4 Member Data Documentation

6.1.4.1 centroids

```
imagetools.ml.KMeans_Custom.centroids
```

6.1.4.2 K

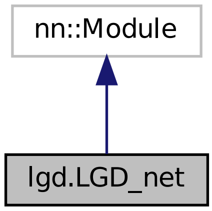
```
imagetools.ml.KMeans_Custom.K
```

The documentation for this class was generated from the following file:

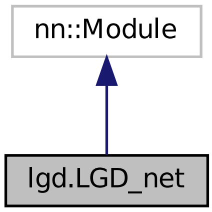
- /home/jhughes2712/projects/image_analysis/jh2284/src/imagetools/ml.py

6.2 lgd.LGD_net Class Reference

Inheritance diagram for lgd.LGD_net:



Collaboration diagram for lgd.LGD_net:



Public Member Functions

- def __init__ (self, niter=5, step_size=step_size)
- def forward (self, y, x_init)

Public Attributes

- niter
- prox
- step_size
- fwd_op_torch
- adj_op_torch

6.2.1 Constructor & Destructor Documentation

6.2.1.1 __init__()

```
def lgd.LGD_net.__init__ (
              self,
              niter = 5,
              step_size = step_size )
```

6.2.2 Member Function Documentation

6.2.2.1 forward()

```
def lgd.LGD_net.forward (
              self,
              y,
              x_init )
```

6.2.3 Member Data Documentation

6.2.3.1 adj_op_torch

```
lgd.LGD_net.adj_op_torch
```

6.2.3.2 fwd_op_torch

```
lgd.LGD_net.fwd_op_torch
```

6.2.3.3 niter

```
lgd.LGD_net.niter
```

6.2.3.4 prox

```
lgd.LGD_net.prox
```

6.2.3.5 step_size

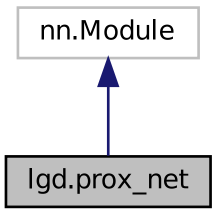
`lgd.LGD_net.step_size`

The documentation for this class was generated from the following file:

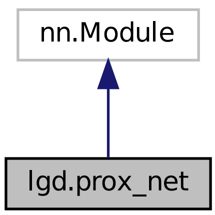
- /home/jhughes2712/projects/image_analysis/jh2284/src/lgd.py

6.3 lgd.prox_net Class Reference

Inheritance diagram for lgd.prox_net:



Collaboration diagram for lgd.prox_net:



Public Member Functions

- def __init__ (self, n_in_channels=2, n_out_channels=1, n_filters=32, kernel_size=3)
- def forward (self, x, u)

Public Attributes

- pad
- conv1
- conv2
- conv3
- act1
- act2

6.3.1 Constructor & Destructor Documentation

6.3.1.1 __init__()

```
def lgd.prox_net.__init__ (
            self,
            n_in_channels = 2,
            n_out_channels = 1,
            n_filters = 32,
            kernel_size = 3 )
```

6.3.2 Member Function Documentation

6.3.2.1 forward()

```
def lgd.prox_net.forward (
            self,
            x,
            u )
```

############ YOUR CODE HERE

6.3.3 Member Data Documentation

6.3.3.1 act1

```
lgd.prox_net.act1
```

6.3.3.2 act2

`lgd.prox_net.act2`

6.3.3.3 conv1

`lgd.prox_net.conv1`

6.3.3.4 conv2

`lgd.prox_net.conv2`

6.3.3.5 conv3

`lgd.prox_net.conv3`

6.3.3.6 pad

`lgd.prox_net.pad`

The documentation for this class was generated from the following file:

- /home/jhughes2712/projects/image_analysis/jh2284/src/lgd.py

Chapter 7

File Documentation

7.1 /home/jhughes2712/projects/image_↩ analysis/jh2284/src/imagetools/__init__.py File Reference

Namespaces

- imagetools

7.2 /home/jhughes2712/projects/image_↩ analysis/jh2284/src/imagetools/ml.py File Reference

Module containing implementations of machine learning algorithms.

Classes

- class imagetools.ml.KMeans_Custom

  Implements a class that handles KMeans Clustering.

Namespaces

- imagetools.ml

Functions

- def imagetools.ml.gradient_descent (obj, grad, x0, obj_min, eps, lr, max_iters, filename)

  Implements vanilla gradient descent for scalar functions on R2.

7.2.1 Detailed Description

Module containing implementations of machine learning algorithms.

Uses numpy to implement KMeans and Gradient Descent, in a way which is not as optimised as, say, scikit-learn, but is readable.

Author

Created by J. Hughes on 8th June 2024.

7.3 /home/jhughes2712/projects/image_↩ analysis/jh2284/src/imagetools/plotting.py File Reference

Module building on matplotlib to provide image-specific plotting functions.

Namespaces

- imagetools.plotting

Functions

- def imagetools.plotting.plot_image (ax_sp, img, title, cmap, gt=None)

7.3.1 Detailed Description

Module building on matplotlib to provide image-specific plotting functions.

Author

Created by J. Hughes on 8th June 2024.

7.4 /home/jhughes2712/projects/image_↩ analysis/jh2284/src/imagetools/signals.py File Reference

Module providing useful functions for image processing when employing Fourier and Wavelet transforms.

Namespaces

- imagetools.signals

Functions

- def imagetools.signals.iterative_soft_thresholding (data_sampled, lam, n_iters, gt=None)

  Implements ISTA in 1D.
- def imagetools.signals.fft1c (x)
- def imagetools.signals.ifft1c (y)
- def imagetools.signals.ComplexSoftThresh (y, lam)
- def imagetools.signals.coeffs2img (LL, coeffs)
- def imagetools.signals.img2coeffs (Wim, levels=4)
- def imagetools.signals.unstack_coeffs (Wim)
- def imagetools.signals.dwt2 (im)
- def imagetools.signals.idwt2 (Wim)

7.4.1 Detailed Description

Module providing useful functions for image processing when employing Fourier and Wavelet transforms.

Many of the functions are taken from the 'helper' module provided on the Image Analysis course GitLab page.

Author

Created by J. Hughes on 8th June 2024.

7.5 /home/jhughes2712/projects/image_analysis/jh2284/src/inverse_problems.py File Reference

Script running code for questions 2.1, 2.2, 2.3, and 3.1.

Namespaces

- inverse_problems

Variables

- inverse_problems.file_list = f.read().split("\n")[:-1]
- inverse_problems.y_noisy = np.array([float(x) for x in file_list])
- inverse_problems.y_outlier = np.array([float(x) for x in file_list])
- inverse_problems.x = np.arange(len(y_noisy))
- inverse_problems.a_noisy_l2 = np.sum(x ∗ y_noisy) / np.sum(x ∗ x)
- inverse_problems.b_noisy_l2 = np.mean(y_noisy) - a_noisy_l2 ∗ np.mean(x)
- inverse_problems.a_outlier_l2 = np.sum(x ∗ y_outlier) / np.sum(x ∗ x)
- inverse_problems.b_outlier_l2 = np.mean(y_outlier) - a_outlier_l2 ∗ np.mean(x)
- inverse_problems.fig
- inverse_problems.ax
- inverse_problems.figsize
- list inverse_problems.B_coefs = [ ]
- inverse_problems.obj_l1 = lambda B: np.sum(np.abs(B[0] ∗ x + B[1] - y))
- inverse_problems.grad_l1
- inverse_problems.B0 = np.array([0.1, 0.1])

- float inverse_problems.lr = 0.0001
- inverse_problems.B = gradient_descent(obj_l1, grad_l1, B0, 0, 0.01, lr, 100, "gd_l1")
- inverse_problems.rng = np.random.default_rng(seed=42)
- inverse_problems.signal = np.zeros(100)
- inverse_problems.data = fft1c(signal)
- int inverse_problems.sample_freq = 4
- inverse_problems.mask_random = rng.uniform(0, 1, 100)
- inverse_problems.mask_unif = np.zeros(100)
- inverse_problems.start_index = rng.integers(0, sample_freq)
- inverse_problems.sample_random = mask_random ∗ data
- inverse_problems.sample_unif = mask_unif ∗ data
- int inverse_problems.signal_random = ifft1c(sample_random) ∗ sample_freq
- int inverse_problems.signal_unif = ifft1c(sample_unif) ∗ sample_freq
- inverse_problems.data_random_recon
- inverse_problems.mse_random
- inverse_problems.lam
- inverse_problems.n_iters = 1000
- inverse_problems.gt
- inverse_problems.data_unif_recon
- inverse_problems.mse_unif
- int inverse_problems.signal_random_recon = ifft1c(data_random_recon) ∗ sample_freq
- int inverse_problems.signal_unif_recon = ifft1c(data_unif_recon) ∗ sample_freq
- inverse_problems.label
- inverse_problems.title
- inverse_problems.xlabel
- inverse_problems.ylabel
- inverse_problems.river_img = skimage.io.imread("data/river_side.jpeg")
- inverse_problems.river_img_dw = dwt2(river_img)
- inverse_problems.river_img_recon = idwt2(river_img_dw)
- inverse_problems.th = np.quantile(abs(river_img_dw), 0.85)
- inverse_problems.river_img_dw_th = abs(river_img_dw) > th
- tuple inverse_problems.plotrange
- inverse_problems.aximg0 = ax[0].imshow(abs(river_img_dw), vmin=plotrange[0], vmax=plotrange[1])
- inverse_problems.aximg1 = ax[1].imshow(abs(river_img_dw_th), cmap="grey")
- float inverse_problems.obj = lambda x: 0.5 ∗ (x[0] ∗∗ 2) + (x[1] ∗∗ 2)
- inverse_problems.grad = lambda x: np.array([x[0], 2.0 ∗ x[1]])
- inverse_problems.x0 = np.array([1.0, 1.0])
- float inverse_problems.eps = 0.01
- float inverse_problems.obj_min = 0.0

7.5.1 Detailed Description

Script running code for questions 2.1, 2.2, 2.3, and 3.1.

This script solves various inverse problems related to signal and image processing, employing various iterative strategies and signal transforms.

Author

Created by J. Hughes on 8th June 2024.

7.6 /home/jhughes2712/projects/image_analysis/jh2284/src/lgd.py File Reference

Script for training LGD.

Classes

- class lgd.prox_net
- class lgd.LGD_net

Namespaces

- lgd

Variables

- lgd.parser = argparse.ArgumentParser()
- lgd.type
- lgd.str
- lgd.choices
- lgd.required
- lgd.args = parser.parse_args()
- int lgd.img_size = 256
- lgd.reco_space
- int lgd.num_angles = 30
- lgd.geometry = odl.tomo.parallel_beam_geometry(reco_space, num_angles=num_angles)
- lgd.fwd_op_odl = odl.tomo.RayTransform(reco_space, geometry)
- lgd.fbp_op_odl
- lgd.adj_op_odl = fwd_op_odl.adjoint
- lgd.phantom_odl = odl.phantom.shepp_logan(reco_space, modified=True)
- lgd.data_odl = fwd_op_odl(phantom_odl)
- lgd.fbp_odl = fbp_op_odl(data_odl)
- lgd.phantom_np = phantom_odl.__array__()
- lgd.fbp_np = fbp_odl.__array__()
- lgd.data_np = data_odl.__array__()
- lgd.fig
- lgd.ax
- lgd.figsize
- lgd.gt
- lgd.grad = odl.Gradient(reco_space)
- lgd.L = odl.BroadcastOperator(fwd_op_odl, grad)
- lgd.data_fit = odl.solvers.L2NormSquared(fwd_op_odl.range).translated(data_odl)
- float lgd.lam = 0.015
- float lgd.reg_func = lam ∗ odl.solvers.L1Norm(grad.range)
- lgd.g = odl.solvers.SeparableSum(data_fit, reg_func)
- lgd.f = odl.solvers.ZeroFunctional(L.domain)
- float lgd.op_norm = 1.1 ∗ odl.power_method_opnorm(L, maxiter=20)
- int lgd.niter = 200
- float lgd.sigma = 2.0
- float lgd.tau = sigma / op_norm∗∗2

- lgd.callback
- lgd.x_admm_odl = L.domain.zero()
- lgd.x_admm_np = x_admm_odl.__array__()
- tuple lgd.device
- int lgd.step_size = 1 / op_norm
- lgd.lgd_net = LGD_net().to(device)
- lgd.num_learnable_params
- tuple lgd.y
- tuple lgd.x_init
- tuple lgd.ground_truth
- lgd.mse_loss = torch.nn.MSELoss()
- lgd.optimizer = torch.optim.Adam(lgd_net.parameters(), lr=1e-4)
- int lgd.num_epochs = 2000
- lgd.ckpt = torch.load("outputs/weights_1990.pth", map_location=device)
- int lgd.start_idx = 1989
- lgd.losses = ckpt["losses"]
- int lgd.save_interval = 1
- int lgd.verbose_interval = 1
- lgd.recon = lgd_net(y, x_init)
- lgd.loss = mse_loss(recon, ground_truth)
- dictionary lgd.checkpoint
- string lgd.checkpoint_filepath = f"outputs/weights_{epoch+1:03d}.pth"
- tuple lgd.lgd_recon_np

7.6.1 Detailed Description

Script for training LGD.

Reconstructs CT images using FBP and ADMM, and compares to a data-driven LGD algorithm. Can be run in 'demo' mode, just performing the last 10 epochs of training from a checkpoint, or 'full' mode which runs all 2000 training epochs.

Author

Created by J. Hughes on 8th June 2024.

7.7 /home/jhughes2712/projects/image_analysis/jh2284/src/segment.py File Reference

Script running code for segmentation problems.

Namespaces

- segment

Variables

- segment.fig
- segment.ax
- segment.figsize
- segment.ct_img = skimage.io.imread("data/CT.png")
- segment.ct_threshold = threshold_otsu(ct_img)
- segment.ct_segmented = ct_img > ct_threshold
- segment.se = disk(4)
- segment.ct_mask = remove_small_objects(binary_opening(ct_segmented, se))
- segment.ct_labelled = label(ct_mask == 0)
- segment.ct_props = regionprops(ct_labelled)
- segment.lung_idx = sorted(list(range(3)), key=lambda i: ct_props[i].area)[:2]
- segment.cmap
- segment.coins_img = skimage.io.imread("data/coins.png")
- segment.coins_marked = coins_img.copy()
- segment.coins_pre = rank.median(coins_img, np.ones((1, 7)))
- int segment.coins_segmented = 1 - chan_vese(coins_pre, mu=0.1)
- segment.coins_labelled = label(coins_segmented)
- list segment.desired_coins_idx
- segment.flowers_img = skimage.io.imread("data/noisy_flower.jpg")
- segment.flowers_pre = denoise_tv_bregman(flowers_img, weight=0.5)
- segment.km = KMeans_Custom(K=6)
- segment.flowers_data = flowers_pre[::8, ::8, :].reshape(-1, 3)
- segment.verbose
- segment.flowers_flat = flowers_pre.reshape(-1, 3)
- segment.flowers_segmented = km.predict_cluster(flowers_flat)
- int segment.flowers_purple = 0

7.7.1 Detailed Description

Script running code for segmentation problems.

This script segments the three images given on the question sheet using three different segmentation algorithms.

Author

Created by J. Hughes on 8th June 2024.

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