CTG_dre

February 9, 2023

1 CTG DRE

1st read in the dfa location: https://archive.ics.uci.edu/ml/datasets/cardiotocography

[2]:
```
import sys
import pandas as pd
import numpy as np
import torch
from torch import distributions
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from scipy import optimize
import pickle
import warnings
from copy import deepcopy
# setting path
sys.path.append('..')

from functions.np_classifier_torch import cutoff_bin, power_alpha_calc  # noqa:␣
↪E402
from functions.estimators_torch import kliep_miss_wrap,␣
↪kliep_multi_dim_sep_wrap, kliep_multi_dim_naive_sep_wrap
from functions.estimators_torch import kliep_multi_dim_imp_wrap,␣
↪kliep_multi_dim_sep_imp_wrap  # noqa: E402
from functions.objective_funcs_torch import get_dat_vals_impute,␣
↪get_dat_vals_multidim
from functions.pipeline_funcs import missing_pipeline, full_pipeline, func_adj,␣
↪get_ci, progress, create_standard_miss_func

unif=distributions.Uniform(0,1)
plt.rcParams["figure.facecolor"] = "White"
plt.rcParams["savefig.facecolor"] = "White"

page_width=9
width_height_ratio=3/4

font = {'weight' : 'normal',
```

```
        'size'   : 14}

plt.rc('font', **font)

warnings.filterwarnings("once")
```

[2]:
```
# Read in data
df = pd.read_excel("../real_world_data/CTG.xls",sheet_name="Raw Data")
#Remove unnecssary columns
df_fin = df.iloc[1: , np.arange(6,14).tolist()+[24,26,39]]

null_df = df_fin[df_fin["NSP"]!=1].drop("NSP",axis=1)
alt_df = df_fin[df_fin["NSP"]==1].drop("NSP",axis=1)

df_fin_nodrop=df_fin.drop("NSP",axis=1)

# Get normalisation terms from training tensor
std = np.nanstd(df_fin_nodrop.to_numpy(), axis=0)
m = np.nanmean(df_fin_nodrop.to_numpy(), axis=0)
```

2 Single Examples

2.1 No missing data

[3]:
```
lr = 0.7**(np.floor((np.arange(1000))/100)+1)
temp_nomiss_norm = full_pipeline(
        null_df, alt_df, None, n_altte=100, n_nulltr=237,
        dr_proc = kliep_miss_wrap, dat_val_fun = get_dat_vals_impute,
        maxiter=1000, est_miss=False, lr=lr, alpha=0.1, delta=0.05,
        split_seed=123
        )
temp_nomiss_norm["power_res"]
```

[3]:
```
[[tensor(0.7900), tensor(0.0675)]]
```

2.2 Corrupted Data, known φ

Now try corrupting the data. We will corrupt them in the worst directions possible

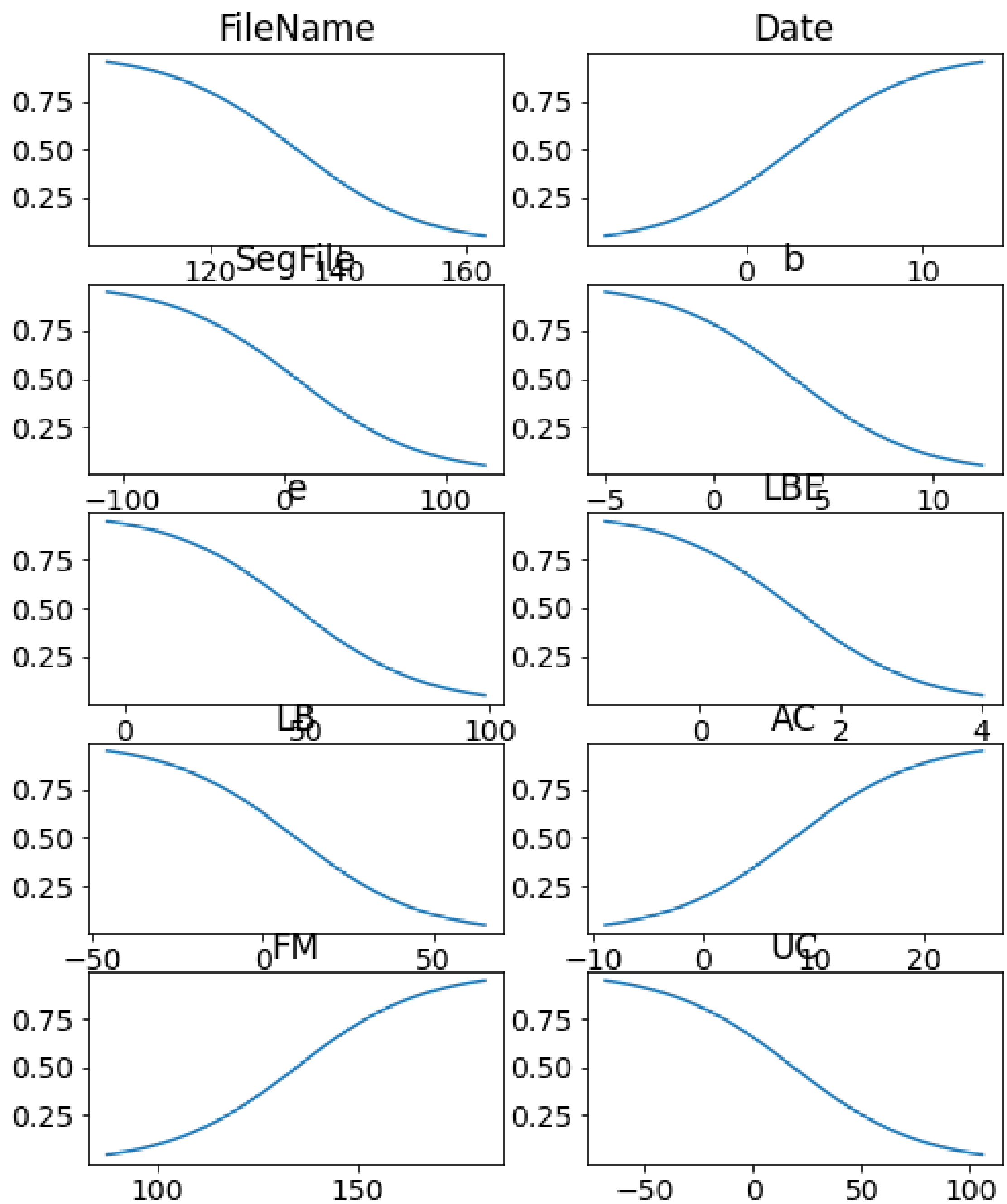
[4]:
```
signs=np.sign(temp_nomiss_norm["dr"]["par"])
missing_funcs = [create_standard_miss_func(m[j],std[j],-signs[j]) for j in␣
 ↪range(10)]
```

Plot these to see what they look like

[5]:
```
print(m.shape)
# adjust true function to be on same scale as normalised data
```

```
fig, ax = plt.subplots(nrows=5,ncols=2,figsize=(8,10))
for j in range(10):
    x=torch.linspace(m[j]-3*std[j],m[j]+3*std[j],50)
    y=missing_funcs[j](x)
    ax[j//2,j%2].plot(x,y)
    ax[j//2,j%2].set(title=df.columns[j])
```

```
(10,)
```



Now try the approach knowing these missing funcs with the same data split and random missing data

[6]:
```
# Test true method
temp_true = full_pipeline(
        null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
        est_miss=False, lr=lr, alpha=0.1, delta=0.05, maxiter=1000,
        split_seed=123, miss_seed=1234)
temp_true["power_res"]
```

[6]: [[tensor(0.6900), tensor(0.0675)]]

We lose a fair amount of power however we now need to see how this compares to the naive approach.

[7]:
```
    # Test naive method
temp_naive = full_pipeline(
        null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_naive_sep_wrap,
        est_miss=False, lr=lr, alpha=0.1, delta=0.05, maxiter=1000,
        split_seed=123, miss_seed=1234)
temp_naive["power_res"]
```

[7]: [[tensor(0.5000), tensor(0.0675)]]

This performs far worse. Out of curiosity see if the reduction in power for our method comes from ultilising the naive assumption more heavily.

[8]:
```
temp_nomiss_nb = full_pipeline(
    null_df, alt_df, None, n_altte=100, n_nulltr=237,
    est_miss=False, lr=lr, alpha=0.1, delta=0.05, maxiter=1000,
    split_seed=123)
temp_nomiss_nb["power_res"]
```

[8]: [[tensor(0.7100), tensor(0.0675)]]

2.3 Iterative Imputation

Now try MICE approach

[9]:
```
mice_args = {"sample_posterior": False, "n_nearest_features": 9}

# Test mice method
temp_mice = full_pipeline(
        null_df, alt_df, missing_funcs=missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_imp_wrap, impute="MICE", mice_args=mice_args,
```

```
        est_miss=False, lr=lr, alpha=0.1, delta=0.05,
        maxiter=1000,
        split_seed=123, miss_seed=1234)
temp_mice["power_res"]
```

[9]: [[tensor(0.7600), tensor(0.0675)]]

This performs surprisingly well. Now, separate each dimension

[17]:
```
mice_args = {"sample_posterior": False, "n_nearest_features": 9}

# Test mice method
temp_mice_naive = full_pipeline(
        null_df, alt_df, missing_funcs=missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_sep_imp_wrap, impute="MICE",␣
 ↪mice_args=mice_args,
        est_miss=False, lr=lr, alpha=0.1, delta=0.05,
        maxiter=1000,
        split_seed=123, miss_seed=1234)
temp_mice_naive["power_res"]
```

[17]: [[tensor(0.5800), tensor(0.0675)]]

We then get our worse performance back again which is interesting. This suggests that marginally our samples are wrong but jointly this is not the case?

2.4 Uniform Imputation

Now try uniform imputation along each

[10]:
```
temp_marg = full_pipeline(
        null_df, alt_df, missing_funcs=missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_imp_wrap, impute="Uniform",
        est_miss=False, lr=lr, alpha=0.1, delta=0.05,
        maxiter=1000,
        split_seed=123, miss_seed=1234)
temp_marg["power_res"]
```

[10]: [[tensor(0.7400), tensor(0.0675)]]

[11]:
```
temp_marg_naive = full_pipeline(
        null_df, alt_df, missing_funcs=missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_sep_imp_wrap, impute="Uniform",
        est_miss=False, lr=lr, alpha=0.1, delta=0.05,
        maxiter=1000,
        split_seed=123, miss_seed=1234)
temp_marg_naive["power_res"]
```

[11]: [[tensor(0.5100), tensor(0.0675)]]

2.5 Weighted Imputation

[12]:
```
temp_marg_weighted = full_pipeline(
        null_df, alt_df, missing_funcs=missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_imp_wrap, impute="Weighted",
        est_miss=False, lr=lr, alpha=0.1, delta=0.05,
        maxiter=1000,
        split_seed=123, miss_seed=1234)
temp_marg_weighted["power_res"]
```

[12]: [[tensor(0.7800), tensor(0.0675)]]

[13]:
```
temp_marg_weighted_naive = full_pipeline(
        null_df, alt_df, missing_funcs=missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_sep_imp_wrap, impute="Weighted",
        est_miss=False, lr=lr, alpha=0.1, delta=0.05,
        maxiter=1000,
        split_seed=123, miss_seed=1234)
temp_marg_weighted_naive["power_res"]
```

[13]: [[tensor(0.6900), tensor(0.0675)]]

That seems to be the case.

2.6 Learning φ

Now try and learn the missingness function. We adapt the ideas of King, Zeng 2001 to do this.

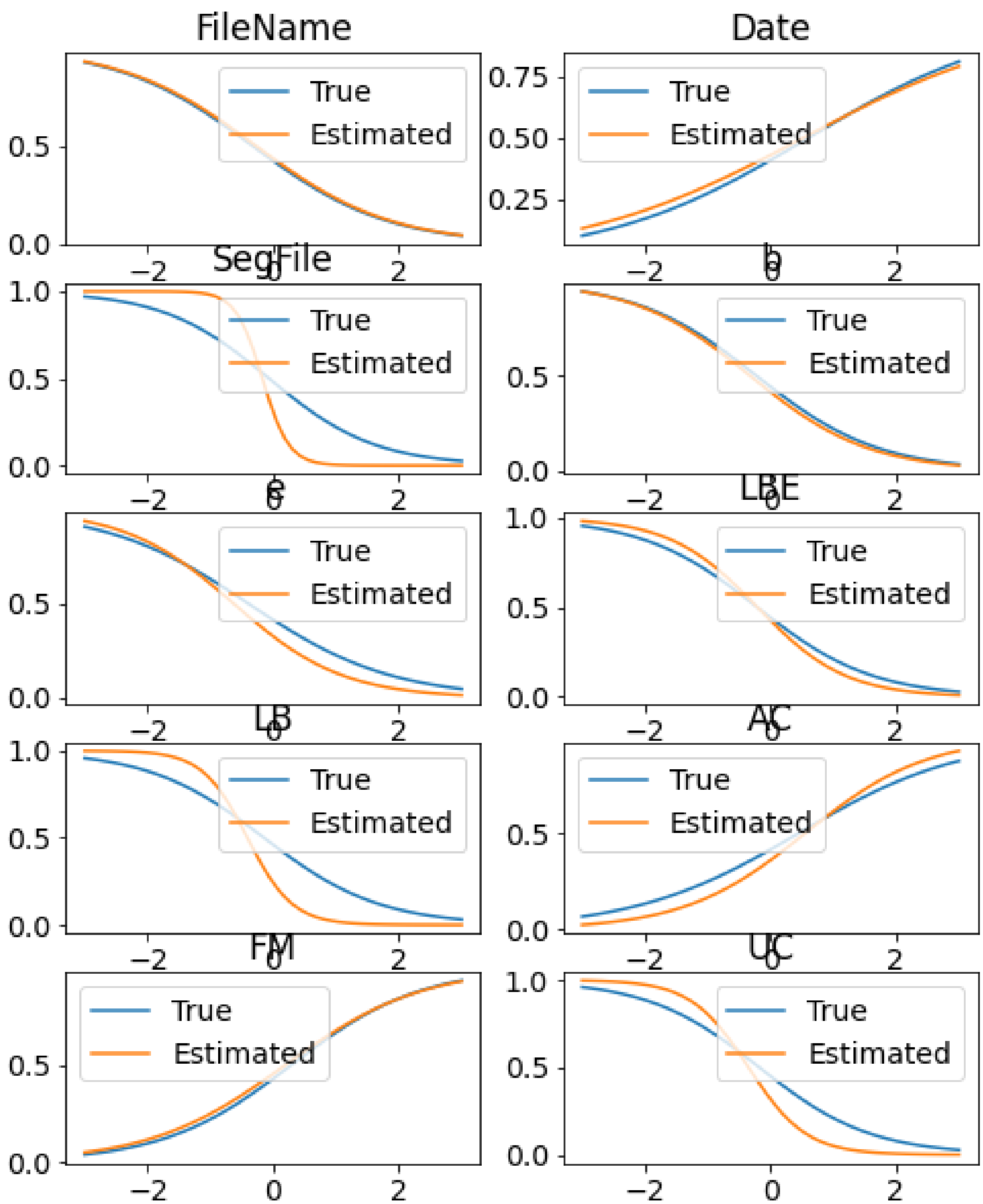
[14]:
```
    # Test our method
temp_our = full_pipeline(
    null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
    est_miss=True, lr=lr,alpha=0.1, delta=0.05, nlearn=25, maxiter=1000,
    split_seed=123,miss_seed=1234,learn_seed=12345)
temp_our["power_res"]
```

[14]: [[tensor(0.7000), tensor(0.0675)]]

Performs identically to method with known missingness funcs!. Out of curiosity plot these missingness funcs against the true ones to compare accuracy.

[23]:
```
adj_miss_funcs = [func_adj(
    temp_our["norm"]["mean"][j], temp_our["norm"]["std"][j], missing_funcs[j]
    ) for j in range(len(missing_funcs))]
fig, ax = plt.subplots(nrows=5, ncols=2, figsize=(8, 10))
for j in range(10):
    x = torch.linspace(-3, 3, 50)
```

```
    y = adj_miss_funcs[j](x)
    y_est = temp_our["est_miss_funcs"][j](x)
    ax[j//2, j % 2].plot(x, y, label="True")
    ax[j//2, j % 2].plot(x, y_est, label="Estimated")
    ax[j//2, j % 2].set(title=df.columns[j])
    ax[j//2, j % 2].legend()
```



Quite good approximation with only 25 points.

3 Repeated Fixed Scenarios

3.1 Random direction missingness

We now try the same procedure but choosing direction of corruption for each feature randomly. We will do this 10 times

[14]:
```
best_meth = []
naive_meth = []
for i in range(1000):
        # ### Chossing missing functions ### #
    signs = torch.multinomial(torch.zeros((2))+1, num_samples=10,
                              replacement=True)
    missing_funcs = [create_standard_miss_func(m[j],std[j],-signs[j]) for j in␣
 ↪range(10)]
# Test new pipeline
    temp_our = full_pipeline(
        null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
        est_miss=True, lr=lr,alpha=0.1, delta=0.05, nlearn=25, maxiter=1000,
        split_seed=123,miss_seed=1234,learn_seed=12345)
    best_meth.append(temp_our["power_res"])

    # Test new pipeline.
    # Test naive method
    temp_naive = full_pipeline(
        null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_naive_sep_wrap,
        est_miss=False, lr=lr, alpha=0.1, delta=0.05, maxiter=1000,
        split_seed=123, miss_seed=1234)
    naive_meth.append(temp_naive["power_res"])

results = {"Learning Missingness Func": best_meth, "Naive": naive_meth}

with open('../results/real_world_results/CTG_missrand_1000sim_ourmeth.pkl',␣
 ↪'wb') as handle:
    pickle.dump(results, handle, protocol=pickle.HIGHEST_PROTOCOL)
```

Give results

[15]:
```
with open('../results/real_world_results/CTG_missrand_1000sim_ourmeth.pkl',␣
 ↪'rb') as handle:
    results = pickle.load(handle)

for key in results:
    print("For "+key+" Method")
    get_ci(torch.tensor(results[key])[:,0])
```

```
For Learning Missingness Func Method
Our Estimated Expected Power is: 0.708
With ci(0.707, 0.708)
For Naive Method
Our Estimated Expected Power is: 0.689
With ci(0.685, 0.692)
```

4 Varying α

Now try all the different approaches each time with completely new data split and for various α.

[27]:
```
warnings.filterwarnings("ignore")
new_meth = []
true_meth = []
best_meth = []
naive_meth = []
nomiss_nb_meth = []
nomiss_norm_meth = []
mice_meth = []
new_seed = 12344
reg = 0
alphas = [0.3,0.25,0.2,0.15,0.1,0.05]
deltas = [0.05]*len(alphas)
mice_args = {"sample_posterior": False, "n_nearest_features": 9}
nsim=1000
for i in range(nsim):
    torch.manual_seed(new_seed)
    # ### Seed Setting ### #
    split_seed = int(1e9*unif.sample([1])[0])
    miss_seed = int(1e9*unif.sample([1])[0])
    learn_seed = int(1e9*unif.sample([1])[0])
    new_seed = int(1e9*unif.sample([1])[0])

    # ### Chossing missing functions ### #
    signs = torch.tensor([-1., 1.])
    signs = signs[torch.multinomial(torch.zeros((2))+1, num_samples=10,
                                    replacement=True)]
    missing_funcs = [create_standard_miss_func(
        m[j], std[j], -signs[j]) for j in range(10)]

    # Test our method
    temp_our = full_pipeline(
        null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
        est_miss=True, lr=lr, alpha=alphas, delta=deltas, nlearn=10,␣
 ↪maxiter=1000,
        reg=reg,
        split_seed=split_seed, miss_seed=miss_seed, learn_seed=learn_seed)
```

```
    # Re-do with smaller LR if errors
    if any(torch.isnan(temp_our["dr"]["par"]).reshape(-1)):
        print(f"Fail on run {i}")
        print(f"Seeds are: Split - {split_seed}, Miss - {miss_seed}, Learn -␣
↪{learn_seed}")
        print(f"Signs are {signs}")
        temp_our = full_pipeline(
            null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
            est_miss=True, lr=0.1*lr, alpha=alphas, delta=deltas, nlearn=10,␣
↪maxiter=1000,
            reg=reg,
            split_seed=split_seed, miss_seed=miss_seed, learn_seed=learn_seed)
        if any(torch.isnan(temp_our["dr"]["par"]).reshape(-1)):
            print(f"Still not Working on run {i}")
    best_meth.append(temp_our["power_res"])

    # Test true method
    temp_true = full_pipeline(
        null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
        est_miss=False, lr=lr, alpha=alphas, delta=deltas, maxiter=1000,
        reg=reg,
        split_seed=split_seed, miss_seed=miss_seed)
    true_meth.append(temp_true["power_res"])

    # Test naive method
    temp_naive = full_pipeline(
        null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_naive_sep_wrap,
        est_miss=False, lr=lr, alpha=alphas, delta=deltas, maxiter=1000,
        reg=reg,
        split_seed=split_seed, miss_seed=miss_seed)
    naive_meth.append(temp_naive["power_res"])

    temp_nomiss_nb = full_pipeline(
        null_df, alt_df, None, n_altte=100, n_nulltr=237,
        est_miss=False, lr=lr, alpha=alphas, delta=deltas, maxiter=1000,
        reg=reg,
        split_seed=split_seed)
    nomiss_nb_meth.append(temp_nomiss_nb["power_res"])

    temp_nomiss_norm = full_pipeline(
        null_df, alt_df, None, n_altte=100, n_nulltr=237,
        dr_proc=kliep_miss_wrap, dat_val_fun=get_dat_vals_impute,
        est_miss=False, lr=lr, alpha=alphas, delta=deltas, maxiter=1000,
        reg=reg,
        split_seed=split_seed)
    nomiss_norm_meth.append(temp_nomiss_norm["power_res"])
```

```
    temp_mice = full_pipeline(
        null_df, alt_df, missing_funcs=missing_funcs, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_sep_imp_wrap, impute="MICE", opt_type="Scalar",
        mice_args=mice_args, est_miss=False, lr=lr, alpha=alphas,
        delta=deltas, maxiter=1000,
        split_seed=split_seed, miss_seed=miss_seed)
    mice_meth.append(temp_mice["power_res"])

    # Print progress
    progress(int(100*(i+1)/nsim))

results = {
    "Learning Missingness Func": best_meth,
    "Naive": naive_meth, "Known Missingness Func": true_meth,
    "No Missing NB": nomiss_nb_meth, "No Missing Normal": nomiss_norm_meth,
    "MICE": mice_meth
}

data = (results,{"alphas": alphas, "deltas": deltas})
with open('../results/real_world_results/
 ↪CTG_fullrand_'+str(nsim)+'sim_allmeth_noreg_varyalpha.pkl', 'wb') as handle:
    pickle.dump(data, handle, protocol=pickle.HIGHEST_PROTOCOL)
```

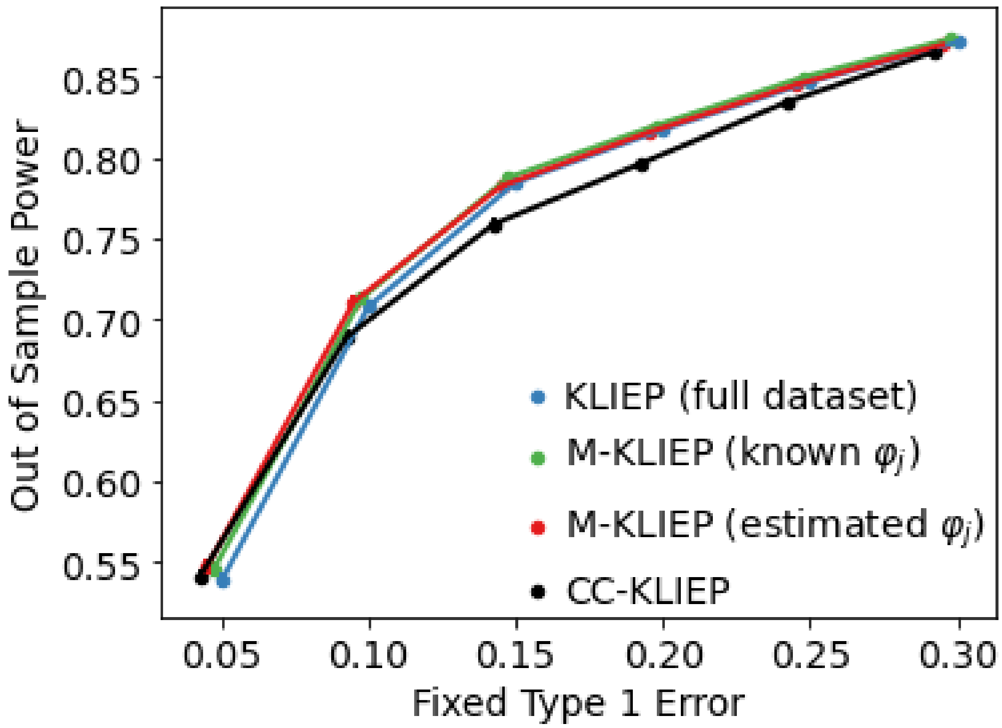
```
[########                                ]22%Fail on run 221
Seeds are: Split - 909081728, Miss - 611009280, Learn - 481309344
Signs are tensor([-1.,  1., -1., -1.,  1., -1., -1.,  1., -1.,  1.])
[################                        ]40%Fail on run 408
Seeds are: Split - 801440256, Miss - 667935808, Learn - 421786080
Signs are tensor([ 1.,  1., -1., -1., -1., -1.,  1., -1.,  1., -1.])
[##########################              ]66%Fail on run 665
Seeds are: Split - 835022400, Miss - 160659008, Learn - 437058912
Signs are tensor([ 1.,  1.,  1.,  1., -1.,  1., -1., -1.,  1., -1.])
[###########################             ]68%Fail on run 683
Seeds are: Split - 452783296, Miss - 392387136, Learn - 926203456
Signs are tensor([-1.,  1., -1., -1., -1.,  1., -1.,  1., -1.,  1.])
[####################################### ]98%Fail on run 988
Seeds are: Split - 19364596, Miss - 473424960, Learn - 765411648
Signs are tensor([-1.,  1., -1., -1.,  1.,  1.,  1., -1.,  1., -1.])
[########################################]100%
```

Give results

[6]:
```
with open('../results/real_world_results/
 ↪CTG_fullrand_1000sim_allmeth_noreg_varyalpha.pkl', 'rb') as handle:
    results, params = pickle.load(handle)

names = {
```

```
    "No Missing NB": "KLIEP (full dataset)",
    "Known Missingness Func": r"M-KLIEP (known $\varphi_j$)",
    "Learning Missingness Func": r"M-KLIEP (estimated $\varphi_j$)",
    "Naive": "CC-KLIEP"
}

cs = [u'#377eb8', u'#4daf4a', u'#e41a1c', u'#000000',u"#984ea3"]
fig, ax = plt.subplots(figsize=(0.7*8, 0.7*6))
for i, key in enumerate(names):
    print(key)
    x = np.array(params["alphas"])
    all_cis = get_ci(torch.tensor(results[key])[:, :, 0],
                     verbose=False)

    y1 = all_cis[1]
    y2 = all_cis[2]
    y = all_cis[0]
    error = y2-y

    diff = x[1]-x[0]

    x_jit = x+diff*0.05*i

    ax.scatter(x_jit, y, label=names[key], s=20, c=cs[i])
    ax.errorbar(x_jit, y, error, c=cs[i],linewidth=2)

ax.set(xlabel="Fixed Type 1 Error", ylabel="Out of Sample Power")
ax.legend(handletextpad=-0.3,borderpad=0, borderaxespad=0.2,frameon=False)

plt.savefig("../plots/np_RWE_CTG_varyalpha.pdf",
            bbox_inches="tight", dpi=300)
```

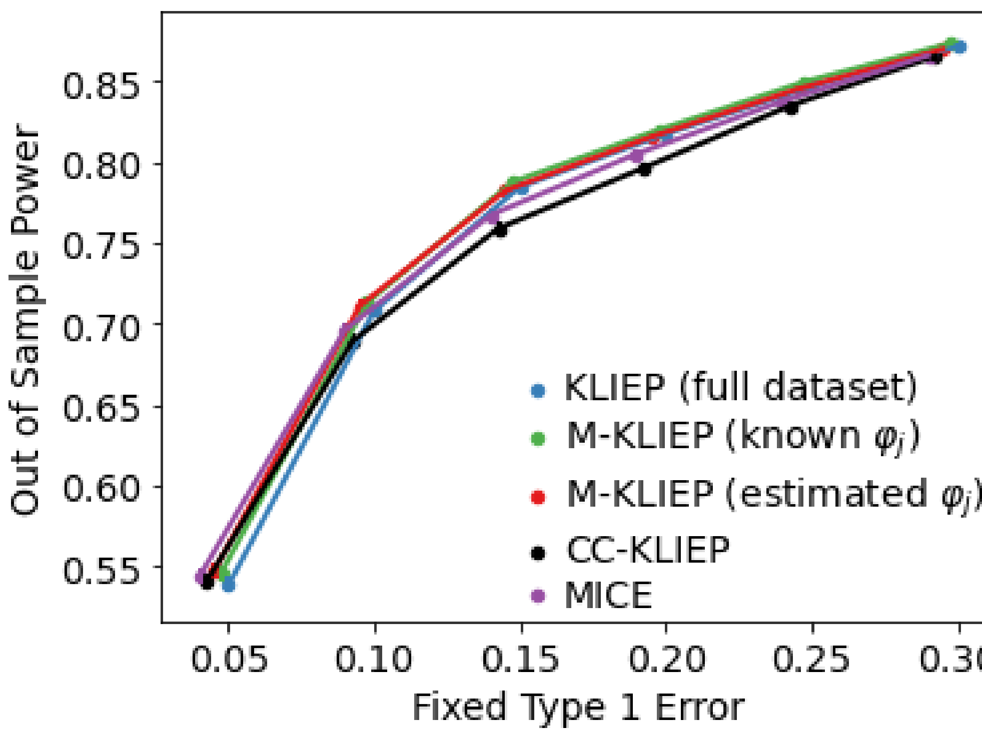
```
No Missing NB
Known Missingness Func
Learning Missingness Func
Naive
```



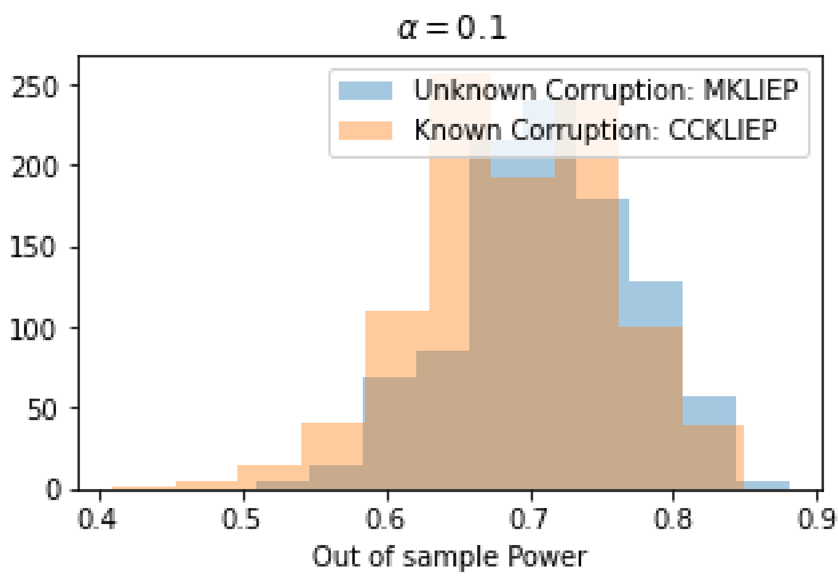
[5]:
```
with open('../results/real_world_results/
↪CTG_fullrand_1000sim_allmeth_noreg_varyalpha.pkl', 'rb') as handle:
    results, params = pickle.load(handle)

names = {
    "No Missing NB": "KLIEP (full dataset)",
    "Known Missingness Func": r"M-KLIEP (known $\varphi_j$)",
    "Learning Missingness Func": r"M-KLIEP (estimated $\varphi_j$)",
    "Naive": "CC-KLIEP",
    "MICE": "MICE"
}

cs = [u'#377eb8', u'#4daf4a', u'#e41a1c', u'#000000',u"#984ea3"]
fig, ax = plt.subplots(figsize=(0.7*8, 0.7*6))
for i, key in enumerate(names):
    print(key)
    x = np.array(params["alphas"])
    all_cis = get_ci(torch.tensor(results[key])[:, :, 0],
                     verbose=False)

    y1 = all_cis[1]
    y2 = all_cis[2]
    y = all_cis[0]
```

```
    error = y2-y

    diff = x[1]-x[0]

    x_jit = x+diff*0.05*i

    ax.scatter(x_jit, y, label=names[key], s=20, c=cs[i])
    ax.errorbar(x_jit, y, error, c=cs[i],linewidth=2)

ax.set(xlabel="Fixed Type 1 Error", ylabel="Out of Sample Power")
ax.legend(handletextpad=-0.3,borderpad=0, borderaxespad=0.2,frameon=False,␣
 ↪labelspacing=0.2)

plt.savefig("../plots/np_RWE_CTG_varyalpha_mice.pdf",
            bbox_inches="tight", dpi=300)
```

```
No Missing NB
Known Missingness Func
Learning Missingness Func
Naive
MICE
```



[22]:
```
results_our = np.array(results["Learning Missingness Func"])[:,4,0]
results_naive = np.array(results["Naive"])[:,4,0]

fig, ax = plt.subplots(figsize=(5, 3))
ax.hist(results_our, alpha=0.4, label='Unknown Corruption: MKLIEP')
ax.hist(results_naive, alpha=0.4, label='Known Corruption: CCKLIEP')
ax.legend(loc='upper right')
ax.set(title=r"$\alpha=$"+str(params["alphas"][4]),xlabel="Out of sample Power")
plt.savefig("../plots/np_RWE_CTG_power_dist.pdf",bbox_inches="tight")
```



5 Varying φ to Vary Proportion Missing

We vary $a_{j,0}$ to vary the proportion of points missing. We now work out what $a_{j,0}$ ti choose to give our desired missing proportions

[15]:
```
def miss_prop_opt(loc,data, m, std, sign, target_prop):
    varphi = create_standard_miss_func(m,std, sign,loc)
    return (torch.nanmean(varphi(data))-target_prop)**2


df_tens = torch.tensor(
    (df_fin_nodrop).to_numpy().astype(np.float32))

locs = []
miss_props = np.arange(0.1,1,0.1)
for miss_prop in miss_props:
    temp_locs = []
```

```
    for j in range(df_fin_nodrop.shape[1]):
        opt_plus = optimize.minimize_scalar(
            miss_prop_opt,args=(df_tens[:,j],m[j],std[j],1.,miss_prop))
        opt_minus = optimize.minimize_scalar(
            miss_prop_opt,args=(df_tens[:,j],m[j],std[j],-1.,miss_prop))

        temp_locs.append([opt_plus["x"], opt_minus["x"]])
    locs.append(temp_locs)
```

We now perform our procedure for these various missing proprtions

[16]:
```
warnings.filterwarnings("ignore")
new_seed = 12345
reg = 0.
alphas = 0.1
deltas = 0.05
nsim = 1000
miss_props = np.arange(0.1,1,0.1)
mice_args = {"sample_posterior": False, "n_nearest_features": 9}
true_meth = {
    key: [[] for j in range(miss_props.shape[0])]
    for key in ["power_res", "prop_miss", "true_prop_miss","grad"]
}

best_meth = deepcopy(true_meth)
naive_meth = deepcopy(true_meth)
mice_meth = deepcopy(true_meth)

for j, miss_prop in enumerate(miss_props):
    for i in range(nsim):
        torch.manual_seed(new_seed)
        # ### Seed Setting ### #
        split_seed = int(1e9*unif.sample([1])[0])
        miss_seed = int(1e9*unif.sample([1])[0])
        learn_seed = int(1e9*unif.sample([1])[0])
        new_seed = int(1e9*unif.sample([1])[0])

        # ### Chossing missing functions ### #
        signs = torch.tensor([-1., 1.])
        signs = signs[torch.multinomial(torch.zeros((2))+1,
         num_samples=df_fin_nodrop.shape[1],
                                        replacement=True)]

        sign_locs = ((signs+1)/2).int()
        missing_funcs = [create_standard_miss_func(
            m[l], std[l], -signs[l], shift=locs[j][l][sign_locs[l]])
            for l in range(df_fin_nodrop.shape[1])]
```

```
        # Test our method
        temp_our = full_pipeline(
            null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
            est_miss=True, alpha=alphas, delta=deltas, nlearn=10, maxiter=100,
            reg=reg, opt_type="scalar",lr=1, tol=1e-3,
            split_seed=split_seed, miss_seed=miss_seed, learn_seed=learn_seed)
        # Re-do with smaller LR if errors
        best_meth["power_res"][j].append(temp_our["power_res"][0])
        best_meth["prop_miss"][j].append(temp_our["prop_miss"])
        best_meth["true_prop_miss"][j].append(miss_prop)
        best_meth["grad"][j].append(temp_our["dr"]["gr"])

        # Test true method
        temp_true = full_pipeline(
            null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
            est_miss=False, alpha=alphas, delta=deltas, maxiter=100,
            reg=reg, opt_type="scalar",lr=1, tol=1e-3,
            split_seed=split_seed, miss_seed=miss_seed)
        true_meth["power_res"][j].append(temp_true["power_res"][0])
        true_meth["prop_miss"][j].append(temp_true["prop_miss"])
        true_meth["true_prop_miss"][j].append(miss_prop)
        true_meth["grad"][j].append(temp_true["dr"]["gr"])

        # Test naive method
        temp_naive = full_pipeline(
            null_df, alt_df, missing_funcs, n_altte=100, n_nulltr=237,
            dr_proc=kliep_multi_dim_naive_sep_wrap,
            est_miss=False, alpha=alphas, delta=deltas, maxiter=100,
            reg=reg, opt_type="scalar",lr=1, tol=1e-3,
            split_seed=split_seed, miss_seed=miss_seed)
        naive_meth["power_res"][j].append(temp_naive["power_res"][0])
        naive_meth["prop_miss"][j].append(temp_naive["prop_miss"])
        naive_meth["true_prop_miss"][j].append(miss_prop)
        naive_meth["grad"][j].append(temp_naive["dr"]["gr"])


        temp_mice = full_pipeline(
            null_df, alt_df, missing_funcs=missing_funcs, n_altte=100,␣
↪n_nulltr=237,
            dr_proc=kliep_multi_dim_sep_imp_wrap, impute="MICE",␣
↪opt_type="Scalar",
            mice_args=mice_args, est_miss=False, lr=lr, alpha=alphas,
            delta=deltas, maxiter=1000,
            split_seed=split_seed, miss_seed=miss_seed)
        mice_meth["power_res"][j].append(temp_mice["power_res"][0])
        mice_meth["prop_miss"][j].append(temp_mice["prop_miss"])
```

```
        mice_meth["true_prop_miss"][j].append(miss_prop)
        mice_meth["grad"][j].append(temp_mice["dr"]["gr"])


        progress(int(100*(j*nsim+(i+1))/(nsim*miss_props.shape[0])))

results = {
    "Learning Missingness Func": best_meth,
    "Naive": naive_meth, "Known Missingness Func": true_meth,
    "Iterative Imputation": mice_meth
}

data = (results, {"alphas": alphas, "deltas": deltas})
with open('../results/real_world_results/
 ↪CTG_fullrand_'+str(nsim)+'sim_allmeth_noreg_varymissfixed_scalar_test.pkl',␣
 ↪'wb') as handle:
    pickle.dump(data, handle, protocol=pickle.HIGHEST_PROTOCOL)
```

```
[########################################]100%
```

Finally perform each procedure with no-missingness as a benchmark.

[19]:
```
new_seed = 12345
reg = 0
alphas = 0.1
deltas = 0.05
nsim = 1000

lr = 0.7**(np.floor((np.arange(1000))/100)+1)

true_meth_0 = {
    key: [[]] for key in ["power_res", "prop_miss", "true_prop_miss","grad"]
}
best_meth_0 = deepcopy(true_meth_0)
naive_meth_0 = deepcopy(true_meth_0)
mice_meth_0 = deepcopy(true_meth_0)
miss_prop=0
for i in range(nsim):
    torch.manual_seed(new_seed)
    # ### Seed Setting ### #
    split_seed = int(1e9*unif.sample([1])[0])
    miss_seed = int(1e9*unif.sample([1])[0])
    learn_seed = int(1e9*unif.sample([1])[0])
    new_seed = int(1e9*unif.sample([1])[0])

    # ### Chossing missing functions ### #
    signs = torch.tensor([-1., 1.])
```

```
    signs = signs[torch.multinomial(torch.zeros((2))+1,␣
↪num_samples=df_fin_nodrop.shape[1],
                                  replacement=True)]

    sign_locs = ((signs+1)/2).int()
    missing_funcs = [create_standard_miss_func(
        m[l], std[l], -signs[l], shift=locs[j][l][sign_locs[l]])
        for l in range(df_fin_nodrop.shape[1])]

    # Test our method
    temp_our = full_pipeline(
        null_df, alt_df, None, n_altte=100, n_nulltr=237,
        est_miss=False, alpha=alphas, delta=deltas, nlearn=10, maxiter=100,
        reg=reg, opt_type="scalar",lr=1, tol=1e-3,
        split_seed=split_seed, miss_seed=miss_seed, learn_seed=learn_seed)
    best_meth_0["power_res"][0].append(temp_our["power_res"][0])
    best_meth_0["prop_miss"][0].append(0)
    best_meth_0["true_prop_miss"][0].append(miss_prop)

    # Test true method
    temp_true = full_pipeline(
        null_df, alt_df, None, n_altte=100, n_nulltr=237,
        est_miss=False, alpha=alphas, delta=deltas, maxiter=100,
        reg=reg, opt_type="scalar",lr=1, tol=1e-3,
        split_seed=split_seed, miss_seed=miss_seed)
    true_meth_0["power_res"][0].append(temp_true["power_res"][0])
    true_meth_0["prop_miss"][0].append(0)
    true_meth_0["true_prop_miss"][0].append(miss_prop)

    # Test naive method
    temp_naive = full_pipeline(
        null_df, alt_df, None, n_altte=100, n_nulltr=237,
        dr_proc=kliep_multi_dim_naive_sep_wrap,
        est_miss=False, alpha=alphas, delta=deltas, maxiter=100,
        reg=reg, opt_type="scalar",lr=1, tol=1e-3,
        split_seed=split_seed, miss_seed=miss_seed)
    naive_meth_0["power_res"][0].append(temp_naive["power_res"][0])
    naive_meth_0["prop_miss"][0].append(0)
    naive_meth_0["true_prop_miss"][0].append(miss_prop)

    temp_mice = full_pipeline(
            null_df, alt_df, missing_funcs=missing_funcs, n_altte=100,␣
↪n_nulltr=237,
            impute=None, opt_type="Scalar",
            mice_args=mice_args, est_miss=False, lr=lr, alpha=alphas,
            delta=deltas, maxiter=1000,
            split_seed=split_seed, miss_seed=miss_seed)
```

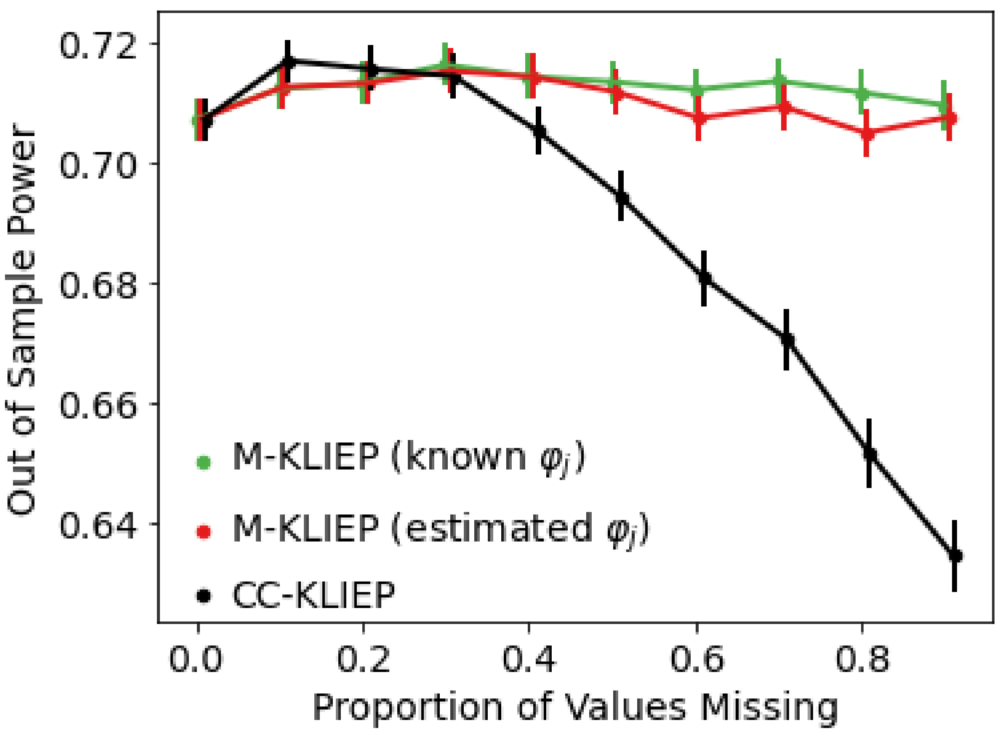
```
    mice_meth_0["power_res"][0].append(temp_mice["power_res"][0])
    mice_meth_0["prop_miss"][0].append(temp_mice["prop_miss"])
    mice_meth_0["true_prop_miss"][0].append(miss_prop)
    mice_meth_0["grad"][0].append(temp_mice["dr"]["gr"])

    progress(int(100*(i+1)/nsim))

results = {
    "Learning Missingness Func": best_meth_0,
    "Naive": naive_meth_0, "Known Missingness Func": true_meth_0,
    "Iterative Imputation": mice_meth_0
}

data = (results, {"alphas": alphas, "deltas": deltas})
with open('../results/real_world_results/
 ↪CTG_fullrand_'+str(nsim)+'sim_allmeth_nomiss_scalar_test.pkl', 'wb') as␣
 ↪handle:
    pickle.dump(data, handle, protocol=pickle.HIGHEST_PROTOCOL)
```

[##] 100%

[9]:

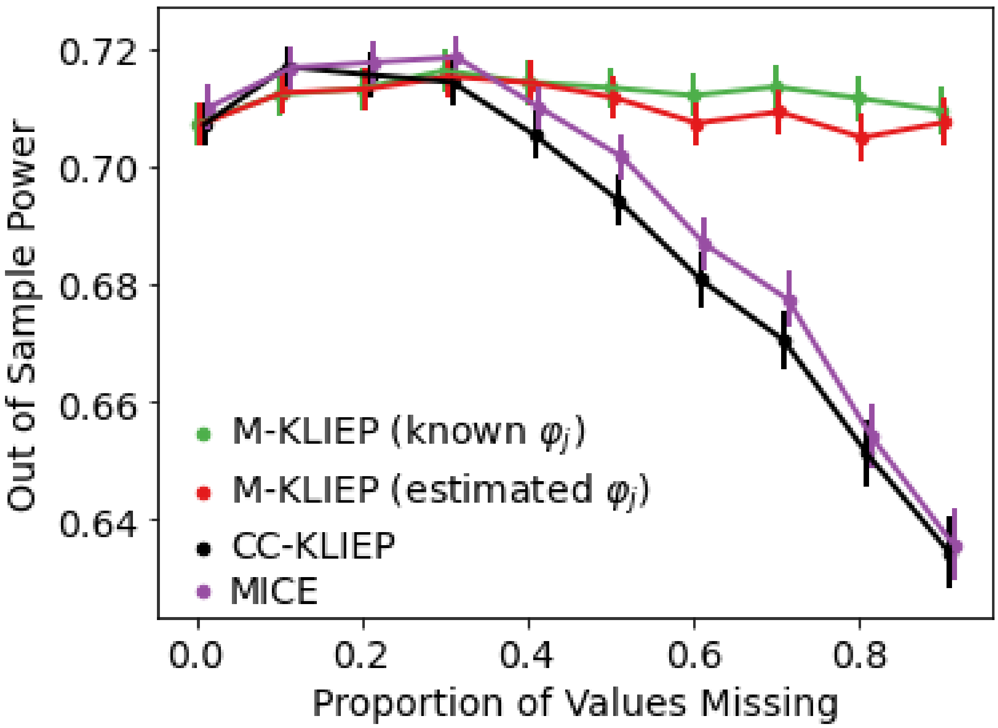
```
with open('../results/real_world_results/
 ↪CTG_fullrand_1000sim_allmeth_nomiss_scalar_test.pkl', 'rb') as handle:
    no_miss_results, params = pickle.load(handle)

with open('../results/real_world_results/
 ↪CTG_fullrand_1000sim_allmeth_noreg_varymissfixed_scalar_test.pkl', 'rb') as␣
 ↪handle:
    results, params = pickle.load(handle)

names = {
    "Known Missingness Func": r"M-KLIEP (known $\varphi_j$)",
    "Learning Missingness Func": r"M-KLIEP (estimated $\varphi_j$) ",
    "Naive": "CC-KLIEP",
}


cs=[u'#377eb8',u'#4daf4a', u'#e41a1c',u'#000000', u"#984ea3"]
fig, ax = plt.subplots(figsize=(0.7*8, 0.7*6))
for i, key in enumerate(names):
    x = torch.mean(torch.
 ↪tensor(no_miss_results[key]["true_prop_miss"]+results[key]["true_prop_miss"]),dim=1)
    all_cis = get_ci(torch.
 ↪tensor(no_miss_results[key]["power_res"]+results[key]["power_res"])[:, :, 0].
 ↪T,
                     verbose=False)
```

```
    y1 = all_cis[1]
    y2 = all_cis[2]
    y = all_cis[0]
    error = y2-y

    diff = x[1]-x[0]

    x_jit = x+diff*0.05*i
    ax.scatter(x_jit, y, label=names[key], s=20,c=cs[i+1])
    ax.errorbar(x_jit, y, error,c=cs[i+1], linewidth=2)

ax.set(xlabel="Proportion of Values Missing", ylabel="Out of Sample Power")
ax.legend(handletextpad=-0.3,borderpad=0, borderaxespad=0.2,frameon=False)

plt.savefig("../plots/np_RWE_CTG_varymissfixed.pdf",
            bbox_inches="tight", dpi=300)
```



[10]:
```
with open('../results/real_world_results/
↪CTG_fullrand_1000sim_allmeth_nomiss_scalar_test.pkl', 'rb') as handle:
    no_miss_results, params = pickle.load(handle)
```

```python
with open('../results/real_world_results/
↪CTG_fullrand_1000sim_allmeth_noreg_varymissfixed_scalar_test.pkl', 'rb') as␣
↪handle:
    results, params = pickle.load(handle)

names = {
    "Known Missingness Func": r"M-KLIEP (known $\varphi_j$)",
    "Learning Missingness Func": r"M-KLIEP (estimated $\varphi_j$) ",
    "Naive": "CC-KLIEP",
    "Iterative Imputation": "MICE"
}


cs=[u'#377eb8',u'#4daf4a', u'#e41a1c',u'#000000', u"#984ea3"]
fig, ax = plt.subplots(figsize=(0.7*8, 0.7*6))
for i, key in enumerate(names):
    x = torch.mean(torch.
↪tensor(no_miss_results[key]["true_prop_miss"]+results[key]["true_prop_miss"]),dim=1)
    all_cis = get_ci(torch.
↪tensor(no_miss_results[key]["power_res"]+results[key]["power_res"])[:, :, 0].
↪T,
                     verbose=False)

    y1 = all_cis[1]
    y2 = all_cis[2]
    y = all_cis[0]
    error = y2-y

    diff = x[1]-x[0]

    x_jit = x+diff*0.05*i
    ax.scatter(x_jit, y, label=names[key], s=20,c=cs[i+1])
    ax.errorbar(x_jit, y, error,c=cs[i+1], linewidth=2)

ax.set(xlabel="Proportion of Values Missing", ylabel="Out of Sample Power")
ax.legend(handletextpad=-0.3,borderpad=0, borderaxespad=0.2,frameon=False,␣
↪labelspacing=0.2)

plt.savefig("../plots/np_RWE_CTG_varymissfixed_mice.pdf",
            bbox_inches="tight", dpi=300)
```


0.72
0.70
0.68
0.66
0.64
Out of Sample Power
M-KLIEP (known φ_j)
M-KLIEP (estimated φ_j)
CC-KLIEP
MICE
0.0
0.2
0.4
0.6
0.8
Proportion of Values Missing