datafusion_progress

February 9, 2022

1 Iterative datafusion

This notebook shows the evolution of posterior kinetic estimates upon iterative addition of more data as it becomes available. It does this by rerunning the analysis for increasingly large experimental datasets, where experiments are added in a chronological fashion.

```
[1]: import numpy as np
     import pandas as pd
     import scipy.stats as stats
     import scipy.optimize as optimize
     import scipy.integrate as integrate
     import sympy as sp
     import ast
     import pymc3 as pm
     import arviz as az
     import theano.tensor as tt
     from numba import njit
     import networkx as nx
     import matplotlib.pyplot as plt
     import matplotlib.gridspec as gridspec
     import matplotlib.patches as mpatches
     import matplotlib.lines as mlines
     import seaborn as sns; sns.set_theme(style='ticks', context='paper',_
      →font_scale=0.8);
     from bayern import ops
     %reload_ext watermark
     %watermark -a "Mathieu Baltussen" -d -t -u -v -iv
```

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```
Python implementation: CPython
    Python version
                   : 3.9.5
                       : 7.28.0
    IPython version
    matplotlib: 3.4.2
             : 3.9.5 | packaged by conda-forge | (default, Jun 19 2021, 00:32:32)
    sys
    [GCC 9.3.0]
           : 3.11.4
    pymc3
    seaborn : 0.11.1
    theano : 1.1.2
    pandas : 1.2.4
            : 1.8
    sympy
    networkx : 2.6.3
            : 1.6.2
    scipy
    bayern
            : 0.1.0
    arviz : 0.11.4
    numpy : 1.20.3
[2]: XSIZE = 7 \#inch
    YSIZE = XSIZE/np.sqrt(2) #inch
    def savefig(name):
         """Helper function to save figures in desired formats"""
        plt.savefig(f"../figures/{name}.svg")
        plt.savefig(f"../figures/{name}.png", dpi=300)
    def generate_figure(n_col, n_row):
         """ Helper function to generate gridspec figures"""
        DX = XSIZE/n_col
        DY = YSIZE/n_col
        YLENGTH = n_row*DY
        fig = plt.figure(figsize=(XSIZE, YLENGTH), constrained_layout=True)
        gs = fig.add_gridspec(n_row, n_col)
        return fig, gs
[3]: import pathlib
    DATA_DIR = pathlib.Path('../data/')
    def load_kinetics_study(code):
        studies_files = DATA_DIR/ 'kinetic_studies.csv'
        studies_df = pd.read_csv(studies_files, index_col=0)
        study = studies df.loc[code]
        data_df = pd.read_csv(DATA_DIR/study.data_path)
        data_df = data_df.assign(**{
            'code': code,
            'kf': study.flowrate/(study.volume*60),
```

```
f'{study.enzyme}': study.enzyme_concentration,
        f'{study.enzyme}_batch': study.bead_batch
    })
    return data_df
def load_network_study(code):
    network_studies = pd.read_csv(f"{DATA_DIR}/network_studies.csv",
        converters={'enzyme_concentration': ast.literal_eval,
                    'bead_batch': ast.literal_eval,
                    'observables': ast.literal_eval
            }, index col=0
    study = network_studies.loc[code]
    return study
def load_HK_studies(studies):
    df_HK = pd.concat([load_kinetics_study(study) for study in studies], u
→ignore_index=True)
    try:
        df_HK.ADP_obs = df_HK.ADP_obs.fillna(df_HK.G6P_obs)
    except AttributeError:
        df_HK = df_HK.assign(
            ADP_obs = df_HK.G6P_obs
    df_HK.G6P_obs = df_HK.G6P_obs.fillna(df_HK.ADP_obs)
    df_HK = df_HK.assign(
        ATP_obs = df_HK.ATP_in - df_HK.G6P_obs,
        G_obs = df_HK.G_in - df_HK.G6P_obs
    return df_HK
def load GDH studies(studies):
    df_GDH = pd.concat([load_kinetics_study(study) for study in studies],_
→ignore_index=True)
    df_GDH = df_GDH.assign(
        NAD_obs = df_GDH.NAD_in - df_GDH.NADH_obs,
        G_obs = df_GDH.G_in - df_GDH.NADH_obs
    )
    return df_GDH
def load_HK_GDH_1_studies(studies):
    df_HK_GDH_1 = []
    for study in studies:
        study_info = load_network_study(study)
```

```
data = pd.read_csv(f"{DATA_DIR}/{study_info.data_path}")
        data = data.assign(
            code = study,
            kf = study_info.flowrate/(study_info.volume*60),
            GDH = study_info.enzyme_concentration[0],
            HK = study_info.enzyme_concentration[1],
            GDH_batch = study_info.bead_batch[0],
            HK_batch = study_info.bead_batch[1]
        )
        data = data.assign(
            G6P obs = lambda x: x["ADP obs"],
            NAD_obs = lambda x: x['NAD_in'] - x['NADH_obs'],
            ATP_obs = lambda x: x['ATP_in'] - x['ADP_obs'],
            G_{obs} = lambda x: x["G_{in}"] - x["ADP_{obs}"] - x["NADH_{obs}"],
        df_HK_GDH_1.append(data)
    df_HK_GDH_1 = pd.concat(df_HK_GDH_1)
    return df_HK_GDH_1
def load_HK_GDH_2_studies(studies):
    df_HK_GDH_2 = []
    for study in studies:
        study info = load network study(study)
        data = pd.read_csv(f"{DATA_DIR}/{study_info.data_path}")
        data = data.assign(
            code = study,
            kf = study_info.flowrate/(study_info.volume*60),
            GDH = study_info.enzyme_concentration[0],
            HK = study_info.enzyme_concentration[1],
            GDH_batch = study_info.bead_batch[0],
            HK_batch = study_info.bead_batch[1]
        )
        df_HK_GDH_2.append(data)
    df_HK_GDH_2 = pd.concat(df_HK_GDH_2)
    return df_HK_GDH_2
```

```
[4]: def load_2_experiments():
    GDH_studies = ["SNCA14", "SNCA15"]

    df_GDH = load_GDH_studies(GDH_studies)

    return df_GDH

def load_3_experiments():
    HK_studies = ["SNCA17"]
    GDH_studies = ["SNCA14", "SNCA15"]
```

```
df_HK = load_HK_studies(HK_studies)
   df_GDH = load_GDH_studies(GDH_studies)
   return df_HK, df_GDH
def load_4_experiments():
   HK_studies = ["SNCA17", "SNCA18"]
   GDH studies = ["SNCA14", "SNCA15"]
   df HK = load HK studies(HK studies)
   df_GDH = load_GDH_studies(GDH_studies)
   return df_HK, df_GDH
def load_5_experiments():
   HK studies = ["SNCA17", "SNCA18", "SNKS03"]
   GDH_studies = ["SNCA14", "SNCA15"]
   df_HK = load_HK_studies(HK_studies)
   df_GDH = load_GDH_studies(GDH_studies)
   return df_HK, df_GDH
def load_6_experiments():
   HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
   GDH_studies = ["SNCA14", "SNCA15"]
   df_HK = load_HK_studies(HK_studies)
   df_GDH = load_GDH_studies(GDH_studies)
   return df_HK, df_GDH
def load_7_experiments():
   HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
   GDH_studies = ["SNCA14", "SNCA15"]
   HK GDH 1 studies = ['SNKS06']
   df HK = load HK studies(HK studies)
   df_GDH = load_GDH_studies(GDH_studies)
   df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
   return df_HK, df_GDH, df_HK_GDH_1
def load_8_experiments():
   HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
```

```
GDH_studies = ["SNCA14", "SNCA15", "SNKS11"]
   HK GDH 1 studies = ['SNKS06']
   df_HK = load_HK_studies(HK_studies)
   df_GDH = load_GDH_studies(GDH_studies)
   df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
   return df HK, df GDH, df HK GDH 1
def load 9 experiments():
   HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
   GDH_studies = ["SNCA14", "SNCA15", "SNKS11", "SNKS12"]
   HK_GDH_1_studies = ['SNKS06']
   df_HK = load_HK_studies(HK_studies)
   df_GDH = load_GDH_studies(GDH_studies)
   df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
   return df_HK, df_GDH, df_HK_GDH_1
def load_10_experiments():
   HK studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
   GDH_studies = ["SNCA14", "SNCA15", "SNKS11", "SNKS12"]
   HK GDH 1 studies = ['SNKS06']
   HK_GDH_2_studies = ['SNNS002']
   df_HK = load_HK_studies(HK_studies)
   df_GDH = load_GDH_studies(GDH_studies)
   df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
   df_HK_GDH_2 = load_HK_GDH_2_studies(HK_GDH_2_studies)
   return df_HK, df_GDH, df_HK_GDH_1, df_HK_GDH_2
def load_11_experiments():
   HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
   GDH studies = ["SNCA14", "SNCA15", "SNKS11", "SNKS12"]
   HK GDH 1 studies = ['SNKS06']
   HK GDH 2 studies = ['SNNS002', 'SNNS003']
   df HK = load HK studies(HK studies)
   df_GDH = load_GDH_studies(GDH_studies)
   df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
   df_HK_GDH_2 = load_HK_GDH_2_studies(HK_GDH_2_studies)
```

```
return df HK, df GDH, df HK GDH 1, df HK GDH 2
def load_12_experiments():
   HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
   GDH_studies = ["SNCA14", "SNCA15", "SNKS11", "SNKS12"]
   HK_GDH_1_studies = ['SNKS06']
   HK_GDH_2_studies = ['SNNS002', 'SNNS003', 'SNNS004']
   df HK = load HK studies(HK studies)
   df_GDH = load_GDH_studies(GDH_studies)
   df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
   df_HK_GDH_2 = load_HK_GDH_2_studies(HK_GDH_2_studies)
   return df_HK, df_GDH, df_HK_GDH_1, df_HK_GDH_2
def load_13_experiments():
   HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
   GDH_studies = ["SNCA14", "SNCA15", "SNKS11", "SNKS12"]
   HK GDH 1 studies = ['SNKS06']
   HK_GDH_2_studies = ['SNNS002', 'SNNS003', 'SNNS004', 'SNNS005']
   df HK = load HK studies(HK studies)
   df GDH = load GDH studies(GDH studies)
   df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
   df_HK_GDH_2 = load_HK_GDH_2_studies(HK_GDH_2_studies)
   return df_HK, df_GDH, df_HK_GDH_1, df_HK_GDH_2
def load 14 experiments():
   HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
   GDH_studies = ["SNCA14", "SNCA15", "SNKS11", "SNKS12"]
   HK_GDH_1_studies = ['SNKS06']
   HK_GDH_2_studies = ['SNNS002', 'SNNS003', 'SNNS004', 'SNNS005', 'SNNS006']
   df HK = load HK studies(HK studies)
   df_GDH = load_GDH_studies(GDH_studies)
   df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
   df_HK_GDH_2 = load_HK_GDH_2_studies(HK_GDH_2_studies)
   return df_HK, df_GDH, df_HK_GDH_1, df_HK_GDH_2
def load_15_experiments():
```

```
HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
         GDH_studies = ["SNCA14", "SNCA15", "SNKS11", "SNKS12"]
         HK GDH 1 studies = ['SNKS06']
         HK_GDH_2_studies = ['SNNS002', 'SNNS003', 'SNNS004', 'SNNS005', 'SNNS006', |

¬'SNNSOO7'

         df HK = load HK studies(HK studies)
         df GDH = load GDH studies(GDH studies)
         df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
         df_HK_GDH_2 = load_HK_GDH_2_studies(HK_GDH_2_studies)
         return df_HK, df_GDH, df_HK_GDH_1, df_HK_GDH_2
     def load 16 experiments():
         HK_studies = ["SNCA17", "SNCA18", "SNKS03", "SNKS04"]
         GDH studies = ["SNCA14", "SNCA15", "SNKS11", "SNKS12", "SNKS18"]
         HK GDH 1 studies = ['SNKS06']
         HK_GDH_2_studies = ['SNNS002', 'SNNS003', 'SNNS004', 'SNNS005', 'SNNS006', |

¬'SNNSOO7'

         df_HK = load_HK_studies(HK_studies)
         df_GDH = load_GDH_studies(GDH_studies)
         df_HK_GDH_1 = load_HK_GDH_1_studies(HK_GDH_1_studies)
         df_HK_GDH_2 = load_HK_GDH_2_studies(HK_GDH_2_studies)
         return df_HK, df_GDH, df_HK_GDH_1, df_HK_GDH_2
[5]: def get_HK_GDH_likelihood(theta_set):
         G, NAD, NADH, ATP = sym_x = sp.symbols("G, NAD, NADH, ATP", real=True)
         k GDH_cat, K_GDH_G, K_GDH_NAD, k_HK_cat, K_HK_G, K_HK_ATP = sym_phi = sp.

→symbols("k_GDH_cat, K_GDH_G, K_GDH_NAD, k_HK_cat, K_HK_G, K_HK_ATP",
□
     →real=True)
         G_in, NAD_in, ATP_in, kf, GDH, HK = sym_theta = sp.symbols("G_in, NAD_in, U
     →ATP_in, kf, GDH, HK", real=True)
         sym_GDH_rate = k_GDH_cat*GDH*G*NAD/((K_GDH_G+G)*(K_GDH_NAD+NAD))
         sym_HK_rate = k_HK_cat*HK*G*ATP/((K_HK_G + G)*(K_HK_ATP+ATP))
         sym_rate_equations = [
             -sym_GDH_rate-sym_HK_rate + kf*(G_in - G),
             -sym_GDH_rate + kf*(NAD_in - NAD),
             +sym GDH rate - kf*NADH,
             -sym_HK_rate + kf*(ATP_in - ATP)
         1
```

```
sym_jac_x = sp.Matrix(sym_rate_equations).jacobian(sym_x)
         sym_jac_phi = sp.Matrix(sym_rate_equations).jacobian(sym_phi)
         sym_jac_theta = sp.Matrix(sym_rate_equations).jacobian(sym_theta)
        t = sp.symbols('t')
        num_rate_equations_ode = njit(sp.lambdify([t, sym_x, sym_phi, sym_theta],_
      →sym_rate_equations, "numpy"))
        num_jac_x_ode = njit(sp.lambdify([t, sym_x, sym_phi, sym_theta], sym_jac_x,_

¬"numpy"))
        num_rate_equations = njit(sp.lambdify([sym_x, sym_phi, sym_theta],_
      →sym rate equations, "numpy"))
        num_jac_x = njit(sp.lambdify([sym_x, sym_phi, sym_theta], sym_jac_x,_
     →"numpy"))
        num_jac_phi = njit(sp.lambdify([sym_x, sym_phi, sym_theta], sym_jac_phi,__
        num_jac_theta = njit(sp.lambdify([sym_x, sym_phi, sym_theta],__
      def find_root(fun, jac, phi, theta):
            return optimize.root(fun=fun, x0=[theta[0],theta[1],0.0, theta[2]],__
     → jac=jac, args=(phi, theta)).x
        num grad phi = njit(lambda x,phi,theta: np.dot(-np.linalg.
      →inv(num_jac_x(x,phi,theta)),num_jac_phi(x,phi,theta)))
        num_grad_theta = njit(lambda x,phi,theta: np.dot(-np.linalg.
      →inv(num_jac_x(x,phi,theta)),num_jac_theta(x,phi,theta)))
        SteadyStateOp = ops.SteadyStateDatasetOp(num_rate_equations, num_jac_x,_
      →num_grad_phi, num_grad_theta, find_root, theta_set=theta_set)
        return SteadyStateOp
[6]: def get simple model(df HK, df GDH):
         exp_HK_idx, exp_HK_coords = df_HK.code.factorize(sort=True)
         exp_GDH_idx, exp_GDH_coords = df_GDH.code.factorize(sort=True)
        batch_GDH idx, batch_GDH_coords = df_GDH.GDH batch.factorize(sort=True)
         coords = {
             "exp_HK": exp_HK_coords,
             "exp_GDH": exp_GDH_coords,
             "batch_GDH": batch_GDH_coords,
        }
        print(f"Topologies: \t4\n\t{len(exp_HK_coords)} experiments_
      →HK\n\t{len(exp_GDH_coords)} experiments GDH")
        print(f"Experiments: \t{len(exp_HK_coords)+len(exp_GDH_coords)}")
```

```
print(f"Datapoints: \t{len(df_HK)+len(df_GDH)}")
   print(f"GDH batches: \t{len(batch GDH coords)}")
   with pm.Model(coords=coords) as model:
       exp_HK_idx = pm.Data("exp_HK_idx", exp_HK_idx)
       exp_GDH_idx = pm.Data("exp_GDH_idx", exp_GDH_idx)
       batch_GDH_idx = pm.Data("batch_GDH_idx", batch_GDH_idx)
       k_cat_hyper = pm.Normal("k_cat_hyper", mu=1500, sigma=500)
       k_GDH_cat = pm.Uniform("k_GDH_cat", 1, k_cat_hyper, dims="batch_GDH")
       k_HK_cat = pm.Uniform("k_HK_cat", 1, k_cat_hyper)
       K_GDH_G = pm.Uniform("K_GDH_G", 1, 20_000)
       K_GDH_NAD = pm.Uniform("K_GDH_NAD", 1, 20_000)
       K_HK_G = pm.Uniform("K_HK_G", 1, 4000)
       K_HK_ATP = pm.Uniform("K_HK_ATP", 1, 6000)
       sigma = pm.Exponential("sigma", 10.0)
       sigma_HK = pm.Exponential("sigma_HK", sigma, dims="exp_HK")
       HK_obs = pm.Normal("HK_obs",
                   mu=(-k HK cat*df HK.HK.values*df HK.G obs.values*df HK.
→ATP_obs.values/(df_HK.kf.values*(K_HK_G+df_HK.G_obs.values)*(K_HK_ATP_+

→df_HK.ATP_obs.values))) + df_HK.G_in.values,
                   sigma=sigma_HK[exp_HK_idx],
                   observed=(df_HK.G_obs.values)
       )
       sigma_GDH = pm.Exponential("sigma_GDH", sigma, dims="exp_GDH")
       GDH obs = pm.Normal("GDH obs",
                   mu=-k_GDH_cat[batch_GDH_idx]*df_GDH.GDH.values*df_GDH.G_obs.
→values*df GDH.NAD obs.values/(
                           df_GDH.kf.values*(K_GDH_G+df_GDH.G_obs.
→values)*(K_GDH_NAD+df_GDH.NAD_obs.values )
                       ) + df_GDH.G_in.values,
                   sigma=sigma GDH[exp GDH idx],
                   observed=(df_GDH.G_obs.values)
       )
   return model
```

```
[7]: def get_GDH_model(df_GDH):
    exp_GDH_idx, exp_GDH_coords = df_GDH.code.factorize(sort=True)

batch_GDH_idx, batch_GDH_coords = df_GDH.GDH_batch.factorize(sort=True)
```

```
coords = {
       "exp_GDH": exp_GDH_coords,
       "batch_GDH": batch_GDH_coords,
   }
   print(f"Topologies: \t\n\t{len(exp_GDH_coords)} experiments GDH")
   print(f"Experiments: \t{len(exp GDH coords)}")
   print(f"Datapoints: \t{len(df_GDH)}")
   print(f"GDH batches: \t{len(batch GDH coords)}")
   with pm.Model(coords=coords) as model:
       exp_GDH_idx = pm.Data("exp_GDH_idx", exp_GDH_idx)
       batch_GDH_idx = pm.Data("batch_GDH_idx", batch_GDH_idx)
       k_cat_hyper = pm.Normal("k_cat_hyper", mu=1500, sigma=500)
       k_GDH_cat = pm.Uniform("k_GDH_cat", 1, k_cat_hyper, dims="batch_GDH")
       K_GDH_G = pm.Uniform("K_GDH_G", 1, 20_000)
       K_GDH_NAD = pm.Uniform("K_GDH_NAD", 1, 20_000)
       sigma_GDH = pm.Exponential("sigma_GDH", 1.0, dims="exp_GDH")
       GDH_obs = pm.Normal("GDH_obs",
                   mu=-k_GDH_cat[batch_GDH_idx]*df_GDH.GDH.values*df_GDH.G_obs.
→values*df GDH.NAD obs.values/(
                           df_GDH.kf.values*(K_GDH_G+df_GDH.G_obs.
→values)*(K_GDH_NAD+df_GDH.NAD_obs.values )
                       ) + df GDH.G in.values,
                   sigma=sigma GDH[exp GDH idx],
                   observed=(df_GDH.G_obs.values)
       )
   return model
```

```
[8]: def get_intermediate_model(df_HK, df_GDH, df_HK_GDH_1):
    exp_HK_idx, exp_HK_coords = df_HK.code.factorize(sort=True)
    exp_GDH_idx, exp_GDH_coords = df_GDH.code.factorize(sort=True)

batch_GDH_idx, batch_GDH_coords = df_GDH.GDH_batch.factorize(sort=True)

exp_HK_GDH_1_idx, exp_HK_GDH_1_coords = df_HK_GDH_1.code.
    factorize(sort=True)

GDH_batch_lookup = dict(zip(batch_GDH_coords, range(len(batch_GDH_coords))))
    batch_GDH_idx_HK_GDH_1 = df_HK_GDH_1.GDH_batch.replace(GDH_batch_lookup).
    values

coords = {
```

```
"exp_HK": exp_HK_coords,
       "exp_GDH": exp_GDH_coords,
       "exp_HK_GDH_1": exp_HK_GDH_1_coords,
       "batch_GDH": batch_GDH_coords,
   }
   print(f"Topologies: \t4\n\t{len(exp_HK_coords)} experiments_
→HK\n\t{len(exp_GDH_coords)} experiments GDH\n\t{len(exp_HK_GDH_1_coords)}_⊔
⇔experiments HK+GDH (complete observability)")
   print(f"Experiments:
→\t{len(exp_HK_coords)+len(exp_GDH_coords)+len(exp_HK_GDH_1_coords)}")
   print(f"Datapoints: \t{len(df HK)+len(df GDH)+len(df HK GDH 1)}")
   print(f"GDH batches: \t{len(batch GDH coords)}")
   with pm.Model(coords=coords) as model:
       exp_HK_idx = pm.Data("exp_HK_idx", exp_HK_idx)
       exp_GDH_idx = pm.Data("exp_GDH_idx", exp_GDH_idx)
       exp_HK_GDH_1_idx = pm.Data("exp_HK_GDH_1_idx", exp_HK_GDH_1_idx)
       batch_GDH_idx = pm.Data("batch_GDH_idx", batch_GDH_idx)
       batch_GDH_idx_HK_GDH_1 = pm.Data("batch_GDH_idx_HK_GDH_1",__
→batch_GDH_idx_HK_GDH_1)
       k_cat_hyper = pm.Normal("k_cat_hyper", mu=1500, sigma=500)
       k_GDH_cat = pm.Uniform("k_GDH_cat", 1, k_cat_hyper, dims="batch_GDH")
       k_HK_cat = pm.Uniform("k_HK_cat", 1, k_cat_hyper)
       K_GDH_G = pm.Uniform("K_GDH_G", 1, 20_000)
       K GDH NAD = pm.Uniform("K GDH NAD", 1, 20 000)
       K_HK_G = pm.Uniform("K_HK_G", 1, 4000)
       K_{HK\_ATP} = pm.Uniform("K\_HK\_ATP", 1, 6000)
       sigma = pm.Exponential("sigma", 10.0)
       sigma_HK = pm.Exponential("sigma_HK", sigma, dims="exp_HK")
       HK obs = pm.Normal("HK obs",
                   mu=(-k_HK_cat*df_HK.HK.values*df_HK.G_obs.values*df_HK.
→ATP obs.values/(df HK.kf.values*(K HK G+df HK.G obs.values)*(K HK ATP +
→df_HK.ATP_obs.values))) + df_HK.G_in.values,
                   sigma=sigma_HK[exp_HK_idx],
                   observed=(df_HK.G_obs.values)
       )
       sigma_GDH = pm.Exponential("sigma_GDH", sigma, dims="exp_GDH")
       GDH_obs = pm.Normal("GDH_obs",
```

```
→values*df GDH.NAD obs.values/(
                                 df_GDH.kf.values*(K_GDH_G+df_GDH.G_obs.
     →values)*(K GDH NAD+df GDH.NAD obs.values )
                             ) + df_GDH.G_in.values,
                         sigma=sigma_GDH[exp_GDH_idx],
                         observed=(df_GDH.G_obs.values)
             )
             sigma_HK_GDH_1 = pm.Exponential("sigma_HK_GDH_1", sigma,_

    dims="exp_HK_GDH_1")

             HK GDH 1 obs = pm.Normal("HK GDH 1 obs",
                         mu=-k_GDH_cat[batch_GDH_idx_HK_GDH_1]*df_HK_GDH_1.GDH.
     →values*df_HK_GDH_1.G_obs.values*df_HK_GDH_1.NAD_obs.values/(
                             df_HK_GDH_1.kf.values*(K_GDH_G+df_HK_GDH_1.G_obs.
     →values)*(K_GDH_NAD+df_HK_GDH_1.NAD_obs.values)
                         -k HK cat*df HK GDH 1.HK.values*df HK GDH 1.G obs.
      →values*df_HK_GDH_1.ATP_obs.values/(df_HK_GDH_1.kf.values*(K_HK_G+df_HK_GDH_1.
      →G_obs.values)*(K_HK_ATP + df_HK_GDH_1.ATP_obs.values)),
                         sigma=sigma_HK_GDH_1[exp_HK_GDH_1_idx],
                         observed=(df HK GDH 1.G obs.values - df HK GDH 1.G in.
     →values)
             )
         return model
[9]: def get_complex_model(df_HK, df_GDH, df_HK_GDH_1, df_HK_GDH_2):
         exp_HK_idx, exp_HK_coords = df_HK.code.factorize(sort=True)
         exp_GDH_idx, exp_GDH_coords = df_GDH.code.factorize(sort=True)
         batch GDH idx, batch GDH coords = df GDH.GDH batch.factorize(sort=True)
         batch_GDH_idx_HK_GDH_2, batch_GDH_coords_HK_GDH_2 = df_HK_GDH_2.GDH_batch.
      →factorize(sort=True)
         exp_HK_GDH_1_idx, exp_HK_GDH_1_coords = df_HK_GDH_1.code.
     →factorize(sort=True)
         exp_HK_GDH_2_idx, exp_HK_GDH_2_coords = df_HK_GDH_2.code.

→factorize(sort=True)
         GDH_batch lookup = dict(zip(batch_GDH_coords, range(len(batch_GDH_coords))))
         batch_GDH_idx_HK_GDH_1 = df_HK_GDH_1.GDH_batch.replace(GDH_batch_lookup).
     →values
         batch_GDH_idx_HK_GDH_2 = df_HK_GDH_2.GDH_batch.replace(GDH_batch_lookup).
      →values
```

mu=-k_GDH_cat[batch_GDH_idx]*df_GDH.GDH.values*df_GDH.G_obs.

```
coords = {
       "exp_HK": exp_HK_coords,
       "exp_GDH": exp_GDH_coords,
       "exp_HK_GDH_1": exp_HK_GDH_1_coords,
       "exp_HK_GDH_2": exp_HK_GDH_2_coords,
       "batch_GDH": batch_GDH_coords,
   }
   print(f"Topologies: \t4\n\t{len(exp_HK_coords)} experiments_
→HK\n\t{len(exp_GDH_coords)} experiments GDH\n\t{len(exp_HK_GDH_1_coords)}_⊔
→experiments HK+GDH (complete observability)\n\t{len(exp_HK_GDH_2_coords)}_⊔
→experiments HK+GDH (partial observability)")
   print(f"Experiments:
→\t{len(exp_HK_coords)+len(exp_GDH_coords)+len(exp_HK_GDH_1_coords)+len(exp_HK_GDH_2_coords)
   print(f"Datapoints:
→\t{len(df_HK)+len(df_GDH)+len(df_HK_GDH_1)+len(df_HK_GDH_2)}")
   print(f"GDH batches: \t{len(batch_GDH_coords)}")
   with pm.Model(coords=coords) as model:
       exp_HK_idx = pm.Data("exp_HK_idx", exp_HK_idx)
       exp_GDH_idx = pm.Data("exp_GDH_idx", exp_GDH_idx)
       exp_HK_GDH_1_idx = pm.Data("exp_HK_GDH_1_idx", exp_HK_GDH_1_idx)
       exp HK GDH 2 idx = pm.Data("exp HK GDH 2 idx", exp HK GDH 2 idx)
       batch GDH idx = pm.Data("batch GDH idx", batch GDH idx)
       batch_GDH_idx_HK_GDH_1 = pm.Data("batch_GDH_idx_HK_GDH_1",__
→batch_GDH_idx_HK_GDH_1)
       k_cat_hyper = pm.Normal("k_cat_hyper", mu=1500, sigma=500)
       k_GDH_cat = pm.Uniform("k_GDH_cat", 1, k_cat_hyper, dims="batch_GDH")
       k_HK_cat = pm.Uniform("k_HK_cat", 1, k_cat_hyper)
       K GDH G = pm.Uniform("K GDH G", 1, 20 000)
       K_GDH_NAD = pm.Uniform("K_GDH_NAD", 1, 20_000)
       K_HK_G = pm.Uniform("K_HK_G", 1, 4000)
       K_HK_ATP = pm.Uniform("K_HK_ATP", 1, 6000)
       sigma = pm.Exponential("sigma", 10.0)
       sigma_HK = pm.Exponential("sigma_HK", sigma, dims="exp_HK")
       HK_obs = pm.Normal("HK_obs",
                   mu=(-k_HK_cat*df_HK.HK.values*df_HK.G_obs.values*df_HK.
→ATP_obs.values/(df_HK.kf.values*(K_HK_G+df_HK.G_obs.values)*(K_HK_ATP + ⊔

→df_HK.ATP_obs.values))) + df_HK.G_in.values,
                   sigma=sigma_HK[exp_HK_idx],
```

```
observed=(df_HK.G_obs.values)
       )
       sigma_GDH = pm.Exponential("sigma_GDH", sigma, dims="exp_GDH")
       GDH_obs = pm.Normal("GDH_obs",
                   mu=-k_GDH_cat[batch_GDH_idx]*df_GDH.GDH.values*df_GDH.G_obs.
→values*df GDH.NAD obs.values/(
                           {\tt df\_GDH.kf.values*(K\_GDH\_G+df\_GDH.G\_obs.}
→values)*(K_GDH_NAD+df_GDH.NAD_obs.values )
                       ) + df GDH.G in.values,
                   sigma=sigma_GDH[exp_GDH_idx],
                   observed=(df GDH.G obs.values)
       )
       sigma_HK_GDH_1 = pm.Exponential("sigma_HK_GDH_1", sigma,__

    dims="exp_HK_GDH_1")

       HK_GDH_1_obs = pm.Normal("HK_GDH_1_obs",
                   mu=-k_GDH_cat[batch_GDH_idx_HK_GDH_1]*df_HK_GDH_1.GDH.
→values*df_HK_GDH_1.G_obs.values*df_HK_GDH_1.NAD_obs.values/(
                       df HK GDH 1.kf.values*(K GDH G+df HK GDH 1.G obs.
→values)*(K_GDH_NAD+df_HK_GDH_1.NAD_obs.values)
                   -k_HK_cat*df_HK_GDH_1.HK.values*df_HK_GDH_1.G_obs.
→values*df_HK_GDH_1.ATP_obs.values/(df_HK_GDH_1.kf.values*(K_HK_G+df_HK_GDH_1.
→G_obs.values)*(K_HK_ATP + df_HK_GDH_1.ATP_obs.values)),
                   sigma=sigma_HK_GDH_1[exp_HK_GDH_1_idx],
                   observed=(df_HK_GDH_1.G_obs.values - df_HK_GDH_1.G_in.
→values)
       )
       sigma_HK_GDH_2 = pm.Exponential("sigma_HK_GDH_2", sigma,_

dims="exp_HK_GDH_2")

       theta = df_HK_GDH_2[["G_in", "NAD_in", "ATP_in", "kf", "GDH", "HK"]].
→values
       likelihood = get_HK_GDH_likelihood(theta)
       HK_GDH_2_obs = pm.Normal(f"HK_GDH_2_obs",
               mu=likelihood(tt.stack([
                   k_GDH_cat[1], K_GDH_G, K_GDH_NAD, k_HK_cat, K_HK_G, K_HK_ATP
               ]))[:,2],
               sigma=sigma_HK_GDH_2[exp_HK_GDH_2_idx],
               observed=df_HK_GDH_2.NADH_obs.values
       )
   return model
```

```
[10]: def sample 2 experiments():
          df_GDH = load_2_experiments()
          model = get_GDH_model(df_GDH)
          with model:
              inference_data = pm.sample(step=pm.NUTS(target_accept=0.95),
                      return_inferencedata=True,
                      cores=8.
                      tune=1000.
                      draws=1000,
                      init="jitter+adapt_full")
              inference data.to netcdf("idata 2prog.nc")
      def sample 3 experiments():
          df_GDH, df_HK = load_3_experiments()
          model = get_simple_model(df_GDH, df_HK)
          with model:
              inference_data = pm.sample(step=pm.NUTS(target_accept=0.95),
                      return_inferencedata=True,
                      cores=8,
                      tune=1000,
                      draws=1000.
                      init="jitter+adapt_full")
              inference_data.to_netcdf("idata_3prog.nc")
      def sample 4 experiments():
          df_GDH, df_HK = load_4_experiments()
          model = get simple model(df GDH, df HK)
          with model:
              inference_data = pm.sample(step=pm.NUTS(target_accept=0.95),
                      return_inferencedata=True,
                      cores=8,
                      tune=1000,
                      draws=1000,
                      init="jitter+adapt_full")
              inference_data.to_netcdf("idata_4prog.nc")
      def sample_5_experiments():
          df GDH, df HK = load 5 experiments()
          model = get_simple_model(df_GDH, df_HK)
          with model:
              inference_data = pm.sample(step=pm.NUTS(target_accept=0.95),
                      return inferencedata=True,
                      cores=8,
                      tune=1000.
                      draws=1000,
                      init="jitter+adapt_full")
              inference_data.to_netcdf("idata_5prog.nc")
```

```
def sample_6_experiments():
    df_GDH, df_HK = load_6_experiments()
    model = get_simple_model(df_GDH, df_HK)
    with model:
        inference_data = pm.sample(step=pm.NUTS(target_accept=0.95),
                return inferencedata=True,
                cores=8,
                tune=1000,
                draws=1000,
                init="jitter+adapt full")
        inference_data.to_netcdf("idata_6prog.nc")
def sample_7_experiments():
    df_GDH, df_HK, df_HK_GDH_1 = load_7_experiments()
    model = get_intermediate_model(df_GDH, df_HK, df_HK_GDH_1)
    with model:
        inference_data = pm.sample(step=pm.NUTS(target_accept=0.98),
                return_inferencedata=True,
                cores=8,
                tune=1000,
                draws=1000,
                init="jitter+adapt_full")
        inference_data.to_netcdf("idata_7prog.nc")
def sample 8 experiments():
    df GDH, df HK, df HK GDH 1 = load 8 experiments()
    model = get_intermediate_model(df_GDH, df_HK, df_HK_GDH_1)
    with model:
        inference_data = pm.sample(step=pm.NUTS(target_accept=0.98),
                return_inferencedata=True,
                cores=8,
                tune=1000,
                draws=1000,
                init="jitter+adapt_full")
        inference_data.to_netcdf("idata_8prog.nc")
def sample_9_experiments():
    df_GDH, df_HK, df_HK_GDH_1 = load_9_experiments()
    model = get_intermediate_model(df_GDH, df_HK, df_HK_GDH_1)
    with model:
        inference_data = pm.sample(step=pm.NUTS(target_accept=0.98),
                return inferencedata=True,
                cores=8,
                tune=1000,
                draws=1000,
                init="jitter+adapt_full")
```

```
inference_data.to_netcdf("idata_9prog.nc")
def sample 10 experiments():
    df_GDH, df_HK, df_HK_GDH_1, df_HK_GDH_2 = load_10_experiments()
    model = get_complex model(df_GDH, df_HK, df_HK_GDH_1, df_HK_GDH_2)
    with model:
        inference_data = pm.sample(step=pm.NUTS(target_accept=0.98),
                return_inferencedata=True.
                cores=8.
                tune=1000,
                draws=1000.
                init="jitter+adapt_full")
        inference_data.to_netcdf("idata_10prog.nc")
def sample_11_experiments():
    df_GDH, df_HK, df_HK_GDH_1, df_HK_GDH_2 = load_11_experiments()
    model = get_complex model(df GDH, df HK, df HK GDH 1, df HK GDH 2)
    with model:
        inference_data = pm.sample(step=pm.NUTS(target_accept=0.98),
                return inferencedata=True,
                cores=8,
                tune=1000.
                draws=1000,
                init="jitter+adapt full")
        inference_data.to_netcdf("idata_11prog.nc")
def sample 12 experiments():
    df_GDH, df_HK, df_HK_GDH_1, df_HK_GDH_2 = load_12_experiments()
    model = get complex model(df GDH, df HK, df HK GDH 1, df HK GDH 2)
    with model:
        inference_data = pm.sample(step=pm.NUTS(target_accept=0.98),
                return_inferencedata=True,
                cores=8.
                tune=1000,
                draws=1000,
                init="jitter+adapt_full")
        inference data.to netcdf("idata 12prog.nc")
def sample 13 experiments():
    df GDH, df HK, df HK GDH 1, df HK GDH 2 = load 13 experiments()
    model = get_complex_model(df_GDH, df_HK, df_HK_GDH_1, df_HK_GDH_2)
    with model:
        inference data = pm.sample(step=pm.NUTS(target accept=0.98),
                return inferencedata=True,
                cores=8,
                tune=1000,
                draws=1000,
```

```
model = get_complex_model(df_GDH, df_HK, df_HK_GDH_1, df_HK_GDH_2)
          with model:
              inference_data = pm.sample(step=pm.NUTS(target_accept=0.98),
                      return inferencedata=True,
                      cores=8,
                      tune=1000.
                      draws=1000,
                      init="jitter+adapt full")
              inference_data.to_netcdf("idata_14prog.nc")
      def sample_15_experiments():
          df_GDH, df_HK, df_HK_GDH_1, df_HK_GDH_2 = load_15_experiments()
          model = get_complex model(df GDH, df HK, df HK GDH 1, df HK GDH 2)
          with model:
              inference_data = pm.sample(step=pm.NUTS(target_accept=0.98),
                      return_inferencedata=True,
                      cores=8.
                      tune=1000,
                      draws=1000.
                      init="jitter+adapt full")
              inference data.to netcdf("idata 15prog.nc")
      def sample 16 experiments():
          df_GDH, df_HK, df_HK_GDH_1, df_HK_GDH_2 = load_16_experiments()
          model = get_complex model(df GDH, df HK, df HK GDH 1, df HK GDH 2)
          with model:
              inference_data = pm.sample(step=pm.NUTS(target_accept=0.98),
                      return_inferencedata=True,
                      cores=8,
                      tune=1000,
                      draws=1000,
                      init="jitter+adapt full")
              inference_data.to_netcdf("idata_16prog.nc")
[25]: sample_2_experiments()
      sample_3_experiments()
      sample_4_experiments()
      sample_5_experiments()
      sample_6_experiments()
      sample_7_experiments()
      sample_8_experiments()
      sample_9_experiments()
```

init="jitter+adapt_full")
inference_data.to_netcdf("idata_13prog.nc")

df_GDH, df_HK, df_HK_GDH_1, df_HK_GDH_2 = load_14_experiments()

def sample_14_experiments():

```
sample_10_experiments()
sample_11_experiments()
sample_12_experiments()
sample_13_experiments()
sample_14_experiments()
sample_15_experiments()
sample_16_experiments()
Topologies:
        4 experiments HK
        4 experiments GDH
        1 experiments HK+GDH (complete observability)
        1 experiments HK+GDH (partial observability)
Experiments:
                10
Datapoints:
                73
GDH batches:
Multiprocess sampling (8 chains in 8 jobs)
NUTS: [sigma HK GDH 2, sigma HK GDH 1, sigma GDH, sigma HK, sigma, K HK ATP,
K_HK_G, K_GDH_NAD, K_GDH_G, k_HK_cat, k_GDH_cat, k_cat_hyper]
<IPython.core.display.HTML object>
Sampling 8 chains for 1_000 tune and 1_000 draw iterations (8_000 + 8_000 draws
total) took 2037 seconds.
There was 1 divergence after tuning. Increase `target_accept` or reparameterize.
There was 1 divergence after tuning. Increase `target accept` or reparameterize.
There was 1 divergence after tuning. Increase `target_accept` or reparameterize.
There were 7 divergences after tuning. Increase `target_accept` or
reparameterize.
There were 11 divergences after tuning. Increase `target_accept` or
reparameterize.
The number of effective samples is smaller than 25% for some parameters.
Topologies:
        4 experiments HK
        4 experiments GDH
        1 experiments HK+GDH (complete observability)
        2 experiments HK+GDH (partial observability)
Experiments:
Datapoints:
                78
GDH batches:
                2
Multiprocess sampling (8 chains in 8 jobs)
NUTS: [sigma_HK_GDH_2, sigma_HK_GDH_1, sigma_GDH, sigma_HK, sigma, K_HK_ATP,
K_HK_G, K_GDH_NAD, K_GDH_G, k_HK_cat, k_GDH_cat, k_cat_hyper]
<IPython.core.display.HTML object>
Sampling 8 chains for 1_000 tune and 1_000 draw iterations (8_000 + 8_000 draws
```

total) took 2518 seconds.

There were 3 divergences after tuning. Increase `target_accept` or reparameterize.

The number of effective samples is smaller than 25% for some parameters.

Topologies: 4

- 4 experiments HK
- 4 experiments GDH
- 1 experiments HK+GDH (complete observability)
- 3 experiments HK+GDH (partial observability)

Experiments: 12
Datapoints: 83
GDH batches: 2

Multiprocess sampling (8 chains in 8 jobs)

NUTS: [sigma_HK_GDH_2, sigma_HK_GDH_1, sigma_GDH, sigma_HK, sigma, K_HK_ATP, K_HK_G, K_GDH_NAD, K_GDH_G, k_HK_cat, k_GDH_cat, k_cat_hyper]

<IPython.core.display.HTML object>

Sampling 8 chains for 1_000 tune and 1_000 draw iterations ($8_000 + 8_000$ draws total) took 3077 seconds.

There were 4 divergences after tuning. Increase `target_accept` or reparameterize.

There was 1 divergence after tuning. Increase `target_accept` or reparameterize. There was 1 divergence after tuning. Increase `target_accept` or reparameterize. There was 1 divergence after tuning. Increase `target_accept` or reparameterize. The number of effective samples is smaller than 25% for some parameters.

Topologies: 4

- 4 experiments HK
- 4 experiments GDH
- 1 experiments HK+GDH (complete observability)
- 4 experiments HK+GDH (partial observability)

Experiments: 13
Datapoints: 88
GDH batches: 2

Multiprocess sampling (8 chains in 8 jobs)

NUTS: [sigma_HK_GDH_2, sigma_HK_GDH_1, sigma_GDH, sigma_HK, sigma, K_HK_ATP, K_HK_G, K_GDH_NAD, K_GDH_G, k_HK_cat, k_GDH_cat, k_cat_hyper]

<IPython.core.display.HTML object>

Sampling 8 chains for 1_000 tune and 1_000 draw iterations ($8_000 + 8_000$ draws total) took 3419 seconds.

There was 1 divergence after tuning. Increase `target_accept` or reparameterize. There was 1 divergence after tuning. Increase `target_accept` or reparameterize. The number of effective samples is smaller than 25% for some parameters.

Topologies: 4

- 4 experiments HK
- 4 experiments GDH

```
1 experiments HK+GDH (complete observability)
```

5 experiments HK+GDH (partial observability)

Experiments: 14
Datapoints: 93
GDH batches: 2

Multiprocess sampling (8 chains in 8 jobs)

NUTS: [sigma_HK_GDH_2, sigma_HK_GDH_1, sigma_GDH, sigma_HK, sigma, K_HK_ATP, K_HK_G, K_GDH_NAD, K_GDH_G, k_HK_cat, k_GDH_cat, k_cat_hyper]

<IPython.core.display.HTML object>

Sampling 8 chains for 1_000 tune and 1_000 draw iterations ($8_000 + 8_000$ draws total) took 3917 seconds.

There was 1 divergence after tuning. Increase `target_accept` or reparameterize.

There was 1 divergence after tuning. Increase `target_accept` or reparameterize.

There was 1 divergence after tuning. Increase `target_accept` or reparameterize.

There were 9 divergences after tuning. Increase `target_accept` or reparameterize.

There was 1 divergence after tuning. Increase `target_accept` or reparameterize.

Topologies: 4

- 4 experiments HK
- 4 experiments GDH
- 1 experiments HK+GDH (complete observability)
- 6 experiments HK+GDH (partial observability)

Experiments: 15
Datapoints: 108
GDH batches: 2

Multiprocess sampling (8 chains in 8 jobs)

NUTS: [sigma_HK_GDH_2, sigma_HK_GDH_1, sigma_GDH, sigma_HK, sigma, K_HK_ATP, K_HK_G, K_GDH_NAD, K_GDH_G, k_HK_cat, k_GDH_cat, k_cat_hyper]

<IPython.core.display.HTML object>

Sampling 8 chains for 1_000 tune and 1_000 draw iterations ($8_000 + 8_000$ draws total) took 4189 seconds.

There were 3 divergences after tuning. Increase `target_accept` or reparameterize.

There was 1 divergence after tuning. Increase `target_accept` or reparameterize. There were 2 divergences after tuning. Increase `target_accept` or reparameterize.

There was 1 divergence after tuning. Increase `target_accept` or reparameterize.

Topologies: 4

- 4 experiments HK
- 5 experiments GDH
- 1 experiments HK+GDH (complete observability)
- 6 experiments HK+GDH (partial observability)

Experiments: 16

Datapoints: 116 GDH batches: 3

Multiprocess sampling (8 chains in 8 jobs)

NUTS: [sigma_HK_GDH_2, sigma_HK_GDH_1, sigma_GDH, sigma_HK, sigma, K_HK_ATP,
K_HK_G, K_GDH_NAD, K_GDH_G, k_HK_cat, k_GDH_cat, k_cat_hyper]

<IPython.core.display.HTML object>

Sampling 8 chains for 1_000 tune and 1_000 draw iterations ($8_000 + 8_000$ draws total) took 3579 seconds.

The number of effective samples is smaller than 25% for some parameters.

Topologies: 4

4 experiments HK

6 experiments GDH

1 experiments HK+GDH (complete observability)

6 experiments HK+GDH (partial observability)

Experiments: 17
Datapoints: 124
GDH batches: 3

Multiprocess sampling (8 chains in 8 jobs)

NUTS: [sigma_HK_GDH_2, sigma_HK_GDH_1, sigma_GDH, sigma_HK, sigma, K_HK_ATP, K_HK_G, K_GDH_NAD, K_GDH_G, k_HK_cat, k_GDH_cat, k_cat_hyper]

<IPython.core.display.HTML object>

Sampling 8 chains for 1_000 tune and 1_000 draw iterations (8_000 + 8_000 draws total) took 3773 seconds.

There were 16 divergences after tuning. Increase `target_accept` or reparameterize.

The acceptance probability does not match the target. It is 0.9441510026918073, but should be close to 0.98. Try to increase the number of tuning steps. The number of effective samples is smaller than 25% for some parameters.

```
[11]: idata_2prog = az.from_netcdf("idata_2prog.nc")
    idata_3prog = az.from_netcdf("idata_3prog.nc")
    idata_4prog = az.from_netcdf("idata_4prog.nc")
    idata_5prog = az.from_netcdf("idata_5prog.nc")
    idata_6prog = az.from_netcdf("idata_6prog.nc")
    idata_7prog = az.from_netcdf("idata_7prog.nc")
    idata_8prog = az.from_netcdf("idata_8prog.nc")
    idata_9prog = az.from_netcdf("idata_9prog.nc")
    idata_10prog = az.from_netcdf("idata_10prog.nc")
    idata_11prog = az.from_netcdf("idata_11prog.nc")
    idata_12prog = az.from_netcdf("idata_12prog.nc")
    idata_13prog = az.from_netcdf("idata_12prog.nc")
    idata_14prog = az.from_netcdf("idata_13prog.nc")
    idata_15prog = az.from_netcdf("idata_14prog.nc")
    idata_15prog = az.from_netcdf("idata_15prog.nc")
    idata_16prog = az.from_netcdf("idata_16prog.nc")
```

```
posterior_2prog df = idata_2prog.to_dataframe(['posterior'],_
      →include_coords=False) # with GDH
      posterior_3prog_df = idata_3prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK
      posterior_4prog_df = idata_4prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK
      posterior_5prog_df = idata_5prog.to_dataframe(['posterior'],_
      →include_coords=False) # with HK
      posterior_6prog_df = idata_6prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK
      posterior_7prog_df = idata_7prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK, HK+GDH 1
      posterior_8prog_df = idata_8prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK, HK+GDH 1
      posterior_9prog_df = idata_9prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK, HK+GDH 1
      posterior_10prog_df = idata_10prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK, HK+GDH 2
      posterior_11prog_df = idata_11prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK, HK+GDH 2
      posterior_12prog_df = idata_12prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK, HK+GDH 2
      posterior_13prog_df = idata_13prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK, HK+GDH 2
      posterior_14prog_df = idata_14prog.to_dataframe(['posterior'],__
      →include_coords=False) # with HK, HK+GDH 2
      posterior_15prog_df = idata_15prog.to_dataframe(['posterior'],__
       →include_coords=False) # with HK, HK+GDH 2
      posterior_16prog_df = idata_16prog.to_dataframe(['posterior'],_
       →include_coords=False) # with HK, HK+GDH 2
[42]: def plot_ridgeplots(fig, gs, n_plots, data, start_color=0):
         pal = sns.cubehelix_palette(n_plots, start=start_color, rot=-.2, dark=0.4,_u
       \rightarrowlight=0.9)
         axes = [fig.add_subplot(gs[i,0]) for i in range(n_plots)]
         for i in range(n_plots):
             sns.kdeplot(data[i], ax=axes[i], fill=True, clip_on=True, alpha=0.6, __
       sns.kdeplot(data[i], ax=axes[i], fill=False, clip_on=True,__
       x_min, x_max = min(axes[-1].get_xticks()), max(axes[-1].get_xticks())
         y_max = max(max(ax.get_yticks()) for ax in axes)*1.1
```

```
max_yticks = [max(ax.get_yticks()) for ax in axes]
print(max_yticks, max(max(ax.get_yticks()) for ax in axes)*1.1)
for i, ax in enumerate(axes):
    # ax.set_ylim(0, y_max)
    # ymax = max(ax.get_yticks())*(n_plots - i)
    ax.set_ylim(0, y_max)
    ax.set_xlim(x_min, x_max)
    ax.patch.set_alpha(0)

for ax in axes[:-1]:
    ax.axis("off")
    sns.despine(ax=ax, left=True, bottom=True)

axes[-1].set_yticks([])
axes[-1].set_ylabel("")
sns.despine(ax=axes[-1], left=True)

return axes, pal
```

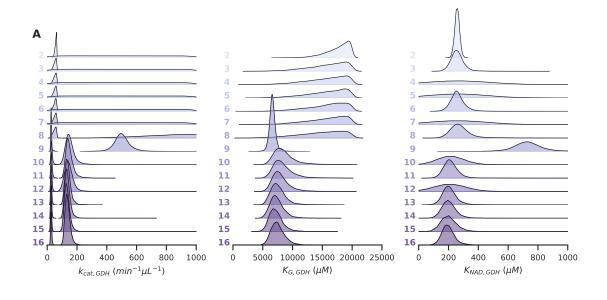
```
[49]: fig, gs = generate_figure(3,2)
      fig.set_constrained_layout(False)
      fig.set_tight_layout(True)
      fig.set_size_inches(XSIZE, YSIZE*1.5)
      HSPACE = -0.8
      N_DATASETS = 15
      gs_rp = gs[0,0].subgridspec(N_DATASETS,1, hspace=HSPACE)
      axes, pal = plot_ridgeplots(fig, gs_rp, N_DATASETS, [
                                                  posterior_2prog_df['k_GDH_cat[0]'],
                                                  posterior_3prog_df['k_GDH_cat[0]'],
                                                  posterior_4prog_df['k_GDH_cat[0]'],
                                                  posterior 5prog df['k GDH cat[0]'],
                                                  posterior_6prog_df['k_GDH_cat[0]'],
                                                  posterior_7prog_df['k_GDH_cat[0]'],
                                                  posterior_8prog_df['k_GDH_cat[0]'],
                                                  posterior_9prog_df['k_GDH_cat[0]'],
                                                  posterior_10prog_df['k_GDH_cat[0]'],
                                                  posterior_11prog_df['k_GDH_cat[0]'],
                                                  posterior_12prog_df['k_GDH_cat[0]'],
                                                  posterior_13prog_df['k_GDH_cat[0]'],
                                                  posterior_14prog_df['k_GDH_cat[0]'],
                                                  posterior_15prog_df['k_GDH_cat[0]'],
                                                  posterior_16prog_df['k_GDH_cat[0]'],
                                  start_color=0.4
      [ax.set_xlim(0, 1000) for ax in axes]
```

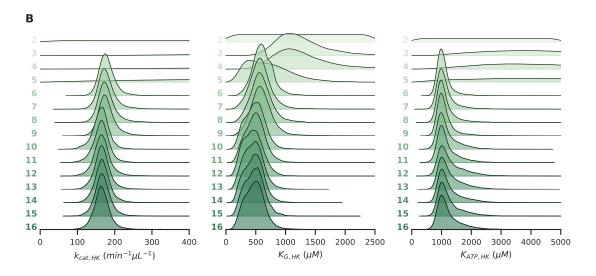
```
axes[-1].set_xlabel("")
axes[-1].axis("off")
axes, pal = plot_ridgeplots(fig, gs_rp, N_DATASETS, [
                                            np.linspace(0, 1000, 8000),
                                            posterior_8prog_df['k_GDH_cat[1]'],
                                            posterior_9prog_df['k_GDH_cat[1]'],
                                            posterior_10prog_df['k_GDH_cat[1]'],
                                            posterior_11prog_df['k_GDH_cat[1]'],
                                            posterior_12prog_df['k_GDH_cat[1]'],
                                            posterior_13prog_df['k_GDH_cat[1]'],
                                            posterior_14prog_df['k_GDH_cat[1]'],
                                            posterior_15prog_df['k_GDH_cat[1]'],
                                            posterior_16prog_df['k_GDH_cat[1]'],
],
                            start_color=0.4
[ax.set_xlim(0, 1000) for ax in axes]
axes[0].text(-0.1, 0.3, 'A', transform=axes[0].transAxes, weight="bold", __
⇒size=10)
for i, ax in enumerate(axes):
    ax.text(-0.02, 0.03, f"{i+2}", fontweight="bold", color=pal[i],
            ha="right", va="center", transform=ax.transAxes)
axes[-1].set_xlabel(r"$k_{cat,GDH}~(min^{-1}\mu L^{-1})$")
gs_rp = gs[0,1].subgridspec(N_DATASETS,1, hspace=HSPACE)
axes, pal = plot_ridgeplots(fig, gs_rp, N_DATASETS, [
                                            posterior 2prog df['K GDH G'],
                                            posterior_3prog_df['K_GDH_G'],
                                            posterior_4prog_df['K_GDH_G'],
                                            posterior_5prog_df['K_GDH_G'],
                                            posterior_6prog_df['K_GDH_G'],
                                            posterior_7prog_df['K_GDH_G'],
                                            posterior_8prog_df['K_GDH_G'],
                                            posterior_9prog_df['K_GDH_G'],
                                            posterior_10prog_df['K_GDH_G'],
                                            posterior_11prog_df['K_GDH_G'],
                                            posterior_12prog_df['K_GDH_G'],
                                            posterior_13prog_df['K_GDH_G'],
                                            posterior_14prog_df['K_GDH_G'],
                                            posterior_15prog_df['K_GDH_G'],
```

```
posterior_16prog_df['K_GDH_G'],
],
                            start color=0.4
[ax.set_xlim(0, 25000) for ax in axes]
for i, ax in enumerate(axes):
    ax.text(-0.02, 0.03, f"{i+2}", fontweight="bold", color=pal[i],
            ha="right", va="center", transform=ax.transAxes)
axes[-1].set xlabel(r"$K {G,GDH}~(\mu M)$")
gs rp = gs[0,2].subgridspec(N DATASETS,1, hspace=HSPACE)
axes, pal = plot_ridgeplots(fig, gs_rp, N_DATASETS, [
                                            posterior_2prog_df['K_GDH_NAD'],
                                            posterior_3prog_df['K_GDH_NAD'],
                                            posterior_4prog_df['K_GDH_NAD'],
                                            posterior_5prog_df['K_GDH_NAD'],
                                            posterior_6prog_df['K_GDH_NAD'],
                                            posterior_7prog_df['K_GDH_NAD'],
                                            posterior_8prog_df['K_GDH_NAD'],
                                            posterior_9prog_df['K_GDH_NAD'],
                                            posterior_10prog_df['K_GDH_NAD'],
                                            posterior_11prog_df['K_GDH_NAD'],
                                            posterior_12prog_df['K_GDH_NAD'],
                                            posterior 13prog df['K GDH NAD'],
                                            posterior_14prog_df['K_GDH_NAD'],
                                            posterior 15prog df['K GDH NAD'],
                                            posterior_16prog_df['K_GDH_NAD'],
],
                            start_color=0.4
[ax.set_xlim(0, 1000) for ax in axes]
for i, ax in enumerate(axes):
    ax.text(-0.02, 0.03, f"{i+2}", fontweight="bold", color=pal[i],
            ha="right", va="center", transform=ax.transAxes)
axes[-1].set_xlabel(r"$K_{NAD,GDH}~(\mu M)$")
gs_rp = gs[1,0].subgridspec(N_DATASETS,1, hspace=HSPACE)
axes, pal = plot_ridgeplots(fig, gs_rp, N_DATASETS, [
                                            np.linspace(0, 1000, 8000),
                                            posterior_3prog_df['k_HK_cat'],
                                            posterior_4prog_df['k_HK_cat'],
                                            posterior_5prog_df['k_HK_cat'],
                                            posterior_6prog_df['k_HK_cat'],
                                            posterior_7prog_df['k_HK_cat'],
                                            posterior_8prog_df['k_HK_cat'],
                                            posterior_9prog_df['k_HK_cat'],
                                            posterior_10prog_df['k_HK_cat'],
```

```
posterior_11prog_df['k_HK_cat'],
                                            posterior_12prog_df['k_HK_cat'],
                                            posterior_13prog_df['k_HK_cat'],
                                            posterior_14prog_df['k_HK_cat'],
                                            posterior_15prog_df['k_HK_cat'],
                                            posterior_16prog_df['k_HK_cat'],
],
                            start_color=2.4
[ax.set xlim(0, 400) for ax in axes]
axes[0].text(-0.1, 0.3, 'B', transform=axes[0].transAxes, weight="bold", ___
⇒size=10)
for i, ax in enumerate(axes):
    ax.text(-0.02, 0.03, f"{i+2}", fontweight="bold", color=pal[i],
            ha="right", va="center", transform=ax.transAxes)
axes[-1].set_xlabel(r"k_{cat,HK}\sim(min^{-1})\L^{-1})")
gs_rp = gs[1,1].subgridspec(N_DATASETS,1, hspace=HSPACE)
axes, pal = plot_ridgeplots(fig, gs_rp, N_DATASETS, [
                                            np.linspace(0, 2500, 8000),
                                            posterior 3prog df['K HK G'],
                                            posterior 4prog df['K HK G'],
                                            posterior_5prog_df['K_HK_G'],
                                            posterior_6prog_df['K_HK_G'],
                                            posterior_7prog_df['K_HK_G'],
                                            posterior_8prog_df['K_HK_G'],
                                            posterior_9prog_df['K_HK_G'],
                                            posterior_10prog_df['K_HK_G'],
                                            posterior_11prog_df['K_HK_G'],
                                            posterior_12prog_df['K_HK_G'],
                                            posterior_13prog_df['K_HK_G'],
                                            posterior_14prog_df['K_HK_G'],
                                            posterior_15prog_df['K_HK_G'],
                                            posterior_16prog_df['K_HK_G'],
                            start_color=2.4
[ax.set_xlim(0, 2500) for ax in axes]
for i, ax in enumerate(axes):
    ax.text(-0.02, 0.03, f"{i+2}", fontweight="bold", color=pal[i],
            ha="right", va="center", transform=ax.transAxes)
axes[-1].set_xlabel(r"$K_{G,HK}^{(mu M)}")
gs_rp = gs[1,2].subgridspec(N_DATASETS,1, hspace=HSPACE)
axes, pal = plot_ridgeplots(fig, gs_rp, N_DATASETS, [
                                            np.linspace(0, 5000, 8000),
                                            posterior_3prog_df['K_HK_ATP'],
```

```
posterior_4prog_df['K_HK_ATP'],
                                                                                            posterior_5prog_df['K_HK_ATP'],
                                                                                            posterior_6prog_df['K_HK_ATP'],
                                                                                            posterior_7prog_df['K_HK_ATP'],
                                                                                            posterior_8prog_df['K_HK_ATP'],
                                                                                            posterior_9prog_df['K_HK_ATP'],
                                                                                            posterior_10prog_df['K_HK_ATP'],
                                                                                            posterior_11prog_df['K_HK_ATP'],
                                                                                            posterior 12prog df['K HK ATP'],
                                                                                            posterior_13prog_df['K_HK_ATP'],
                                                                                            posterior_14prog_df['K_HK_ATP'],
                                                                                            posterior_15prog_df['K_HK_ATP'],
                                                                                            posterior_16prog_df['K_HK_ATP'],
                                                                                            ],
                                                           start_color=2.4
 [ax.set_xlim(0, 5000) for ax in axes]
 for i, ax in enumerate(axes):
         ax.text(-0.02, 0.03, f"{i+2}", fontweight="bold", color=pal[i],
                         ha="right", va="center", transform=ax.transAxes)
 axes[-1].set_xlabel(r"$K_{ATP,HK}^(\mu M)$")
 sns.despine(ax=axes[0], left=False)
 savefig("fig progression")
[0.1, 0.06, 0.06, 0.06, 0.06, 0.06, 0.04, 0.2, 0.1, 0.1, 0.1,
0.1500000000000000, 0.150000000000000, 0.150000000000000,
[0.0015, 0.0015, 0.0015, 0.0015, 0.0015, 0.0015, 0.002, 0.01, 0.02, 0.03, 0.02,
0.03, 0.03, 0.03, 0.03] 0.033
[0.00030000000000000003, 0.0002, 0.0002, 0.0002, 0.0001500000000000001,
0.0001500000000000001, 0.000150000000000001, 0.001, 0.0003000000000000003,
0.0004, 0.0004, 0.0004, 0.0004, 0.0004, 0.0004] 0.0011
[0.03, 0.015, 0.002, 0.003, 0.015, 0.002, 0.0075, 0.006, 0.006, 0.01, 0.004,
0.01, 0.01, 0.01, 0.015] 0.033
[0.0015, 0.0015, 0.0015, 0.0015, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0.03, 0
0.03, 0.03, 0.03] 0.033
[0.000600000000000001, 0.0015, 0.0015, 0.0015, 0.003, 0.003, 0.003, 0.003,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003] 0.0033000000000000004
0.0003000000000000003, 0.003, 0.003, 0.003, 0.003, 0.002, 0.002, 0.002, 0.002,
0.002, 0.002, 0.002] 0.0033000000000000004
```





[]: