

## fig\_toc

February 9, 2022

```
[13]: import numpy as np
import pandas as pd
import scipy.stats as stats
import scipy.optimize as optimize
import pymc3 as pm
import arviz as az
import theano.tensor as tt

import networkx as nx

import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec
import seaborn as sns; sns.set_theme(style='ticks', context='paper',
    ↪font_scale=0.8);

%reload_ext watermark
%watermark -a "Mathieu Baltussen" -d -t -u -v -iv
```

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Python implementation: CPython

Python version : 3.9.5

IPython version : 7.28.0

arviz : 0.11.4

numpy : 1.20.3

networkx : 2.6.3

sys : 3.9.5 | packaged by conda-forge | (default, Jun 19 2021, 00:32:32)  
[GCC 9.3.0]

theano : 1.1.2

scipy : 1.6.2

matplotlib: 3.4.2

pandas : 1.2.4

seaborn : 0.11.1

pymc3 : 3.11.4

```

[2]: data = pd.read_csv("../data/CEKS33.csv")
kf = 0.125 # minute-1
E = 0.012
data = data.assign(kf=kf, Tr=E)
data_1 = data[data.AAA == 0]
data_2 = data[data.AAA != 0]

[3]: with pm.Model() as model_1:
    k_cat = pm.Uniform("k_cat", 0, 500)
    K_M = pm.Uniform("K_M", 0, 500)
    K_I = pm.Uniform("K_I", 1000, 10000)
    sigma = pm.Exponential("sigma", 10)

    S_in = data_1["R"].values
    I_in = data_1["AAA"].values
    P_obs = data_1["AMC"].values
    S_obs = (
        S_in - P_obs
    ) # Substrate concentration inside reactor determined via stoichiometric
    ↪ conservation at steady-state
    E = data_1["Tr"].values
    kf = data_1["kf"].values

    # Inference of probabilistic model at steady-state conditions
    P = pm.Normal(
        "obs",
        mu=k_cat * E * S_obs / (kf * (K_M + S_obs * (1 + I_in / K_I))),
        sigma=sigma,
        observed=P_obs,
    )
    idata_1 = pm.sample(
        1000,
        tune=1000,
        cores=4,
        step=pm.NUTS(target_accept=0.95),
        return_inferencedata=True,
    )

with pm.Model() as model_2:
    k_cat = pm.Uniform("k_cat", 0, 500)
    K_M = pm.Uniform("K_M", 0, 500)
    K_I = pm.Uniform("K_I", 1000, 10000)
    sigma = pm.Exponential("sigma", 10)

    S_in = data_2["R"].values
    I_in = data_2["AAA"].values
    P_obs = data_2["AMC"].values

```

```

S_obs = (
    S_in - P_obs
) # Substrate concentration inside reactor determined via stoichiometric
↪ conservation at steady-state
E = data_2["Tr"].values
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    "obs",
    mu=k_cat * E * S_obs / (kf * (K_M + S_obs * (1 + I_in / K_I))),
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```

```

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        return_inferencedata=True,
    )

```

Multiprocess sampling (4 chains in 4 jobs)

NUTS: [sigma, K\_I, K\_M, k\_cat]

<IPython.core.display.HTML object>

Sampling 4 chains for 1\_000 tune and 1\_000 draw iterations (4\_000 + 4\_000 draws total) took 6 seconds.

Multiprocess sampling (4 chains in 4 jobs)

NUTS: [sigma, K\_I, K\_M, k\_cat]

<IPython.core.display.HTML object>

Sampling 4 chains for 1\_000 tune and 1\_000 draw iterations (4\_000 + 4\_000 draws total) took 13 seconds.

There were 2 divergences 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.

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

Multiprocess sampling (4 chains in 4 jobs)

NUTS: [sigma, K\_I, K\_M, k\_cat]

<IPython.core.display.HTML object>

Sampling 4 chains for 1\_000 tune and 1\_000 draw iterations (4\_000 + 4\_000 draws total) took 4 seconds.

```

[4]: posterior_df_1 = idata_1.to_dataframe(["posterior"])
    posterior_df_2 = idata_2.to_dataframe(["posterior"])
    posterior_df = idata.to_dataframe(["posterior"])

    with model_1:
        post_pred_1 = pm.sample_posterior_predictive(
            idata_1, var_names=["obs", "k_cat", "K_M", "K_I", "sigma"]
        )
    posterior_df_1 = pd.DataFrame(
        {
            "k_cat": post_pred_1["k_cat"],
            "K_M": post_pred_1["K_M"],
            "K_I": post_pred_1["K_I"],
            "sigma": post_pred_1["sigma"],
        }
    )

```

```

with model_2:
    post_pred_2 = pm.sample_posterior_predictive(
        idata_2, var_names=["obs", "k_cat", "K_M", "K_I", "sigma"]
    )
posterior_df_2 = pd.DataFrame(
    {
        "k_cat": post_pred_2["k_cat"],
        "K_M": post_pred_2["K_M"],
        "K_I": post_pred_2["K_I"],
        "sigma": post_pred_2["sigma"],
    }
)
with model:
    post_pred = pm.sample_posterior_predictive(
        idata, var_names=["obs", "k_cat", "K_M", "K_I", "sigma"]
    )
posterior_df = pd.DataFrame(
    {
        "k_cat": post_pred["k_cat"],
        "K_M": post_pred["K_M"],
        "K_I": post_pred["K_I"],
        "sigma": post_pred["sigma"],
    }
)

```

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

```

[25]: left = nx.bipartite.sets(model_graph)[0]
pos = nx.bipartite_layout(model_graph, list(left)[::-1], scale=0.8)
print(pos)

pos = {
    "$\\mathcal{L}_{2}$": np.array([0.25, 0.25]),
    "$\\mathcal{L}_{1}$": np.array([0.25, 0.75]),
    "$k_{cat}$": np.array([0.75, 0.7]),
    "$K_M$": np.array([0.75, 0.5]),
    "$K_I$": np.array([0.75, 0.2]),
}

fig, ax = plt.subplots(constrained_layout=True)

with sns.color_palette("deep"):
    nx.draw(
        model_graph,

```

```

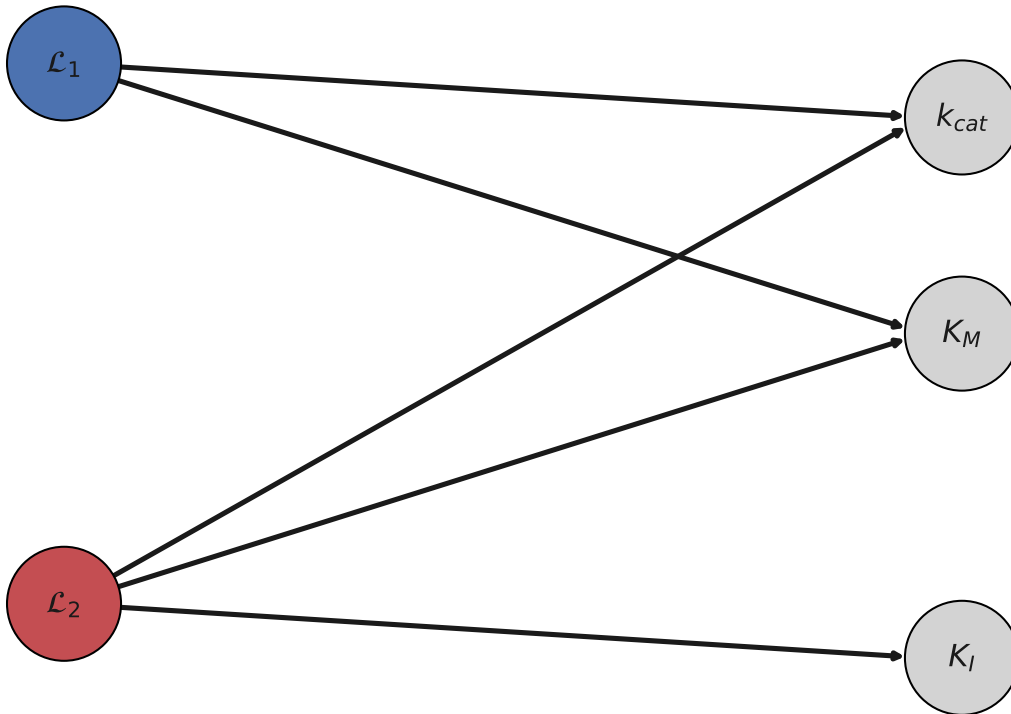
pos=pos,
ax=ax,
with_labels=True,
node_size=2000,
node_color=["C0", "lightgrey", "lightgrey", "C3", "lightgrey"],
width=2,
edgecolors="black",
arrowstyle="->",
arrowsize=6,
connectionstyle="arc,armB=-15",
)

```

```

{'$\mathcal{L}_2$': array([-0.8, -0.5]), '$\mathcal{L}_1$': array([-0.8,
0.5]), '$k_{cat}$': array([ 0.53333333, -0.5      ]), '$K_M$':
array([0.53333333, 0.      ]), '$K_I$': array([0.53333333, 0.5      ])}

```



```

[85]: 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,
    ↪light=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,
↪color=pal[i])
        sns.kdeplot(data[i], ax=axes[i], fill=False, clip_on=True,
↪color="black", lw=.2)

        # y_max = max(max(ax.get_yticks()) for ax in axes)*1.1
        x_min, x_max = min(axes[-1].get_xticks()), max(axes[-1].get_xticks())
        for i, ax in enumerate(axes):
            # ax.set_ylim(0, y_max)
            ymax = max(ax.get_yticks()*(n_plots - i)
            ax.set_ylim(0)
            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

```

```

[114]: palette = sns.cubehelix_palette(3, start=0.4, rot=-.2, dark=0.4, light=0.9)
palette

```

```

[114]: [[0.8785578419340125, 0.9014144832192498, 0.9687173115546507],
        [0.6406706030956623, 0.622799643084166, 0.8302502287527784],
        [0.4428111826648146, 0.3448837880001888, 0.5788669999260483]]

```

```

[218]: model_graph = nx.DiGraph()
model_graph.add_edge(r"$\mathcal{L}_{1}$", r"$k_{cat}$")
model_graph.add_edge(r"$\mathcal{L}_{1}$", r"$K_M$")
model_graph.add_edge(r"$\mathcal{L}_{2}$", r"$k_{cat}$")
model_graph.add_edge(r"$\mathcal{L}_{2}$", r"$K_M$")
model_graph.add_edge(r"$\mathcal{L}_{2}$", r"$K_I$")
pos = {
    "$\mathcal{L}_{2}$": np.array([0.33, 0.425]),
    "$\mathcal{L}_{1}$": np.array([0.33, 0.575]),
    "$k_{cat}$": np.array([0.66, 0.65]),
    "$K_M$": np.array([0.66, 0.5]),
    "$K_I$": np.array([0.66, 0.35]),
}

fig = plt.figure(figsize=(3.25, 1.75), constrained_layout=True)

```

```

gs = fig.add_gridspec(4, 3, wspace=0.2, hspace=0.0)

# gs.subplots()

ax_1 = fig.add_subplot(gs[1:3, 0])
ax_1.scatter(data_1.R, data_1.AMC, ec="black", fc="C0", label=r"[I]=0  $\mu$  M", s=32)
ax_1.scatter(data_2.R, data_2.AMC, ec="black", fc="C3", label=r"[I]=1500  $\mu$  M", s=32)
ax_1.plot(data_1.R, data_1.AMC, "--", c="C0")
ax_1.plot(data_2.R, data_2.AMC, "--", c="C3")
# ax_1.legend()
ax_1.set_xlim(0, 600)
ax_1.set_ylim(0, 9)
# ax_1.text(-0.18, 0.95, 'A', transform=ax_1.transAxes, weight="bold", size=10)
ax_1.set_xlabel(r" $[\text{S}]_{\text{in}}$ ")
ax_1.set_ylabel(r" $[\text{P}]_{\text{out}}$ ")
ax_1.set_xticks([])
ax_1.set_yticks([])
sns.despine(ax=ax_1)
ax_1.margins(y=-0.3)

ax_2 = fig.add_subplot(gs[:, 1])

with sns.color_palette("deep"):
    nx.draw(
        model_graph,
        pos=pos,
        ax=ax_2,
        with_labels=True,
        node_size=400,
        node_color=["C0", palette[1], palette[1], "C3", palette[1]],
        width=1,
        edgecolors="black",
        arrowstyle="->",
        arrowsize=9,
        connectionstyle="arc",
        font_size=10
    )
ax_2.margins(x=0.25, y=0.1)

ax_3 = fig.add_subplot(gs[0:2, 2:])

sns.kdeplot(posterior_df_1["k_cat"], ax=ax_3, fill=True, color="C0")
sns.kdeplot(posterior_df_2["k_cat"], ax=ax_3, fill=True, color="C3")

```



```

sns.kdeplot(posterior_df["k_cat"], ax=ax_3, fill=True, color=palette[2],
↳alpha=0.5)
sns.despine(ax=ax_3)
ax_3.set_xlim(75, 120)
ax_3.set_ylabel(r"$P(k_{cat}|\mathbf{y})$")
ax_3.set_xlabel(r"$k_{cat}$")
ax_3.set_xticks([])
ax_3.set_yticks([])

# gs_rp = gs[2:, 2].subgridspec(3,1, hspace=-0.1)
# axes, pal = plot_ridgeplots(fig, gs_rp, 3, [
#                                     posterior_df_1['K_I'],
#                                     posterior_df_2['K_I'],
#                                     posterior_df['K_I']],
#                               start_color=0.4
#                               )

ax_4 = fig.add_subplot(gs[2:, 2])

sns.kdeplot(posterior_df_1["K_I"], ax=ax_4, fill=True, color="C0")
sns.kdeplot(posterior_df_2["K_I"], ax=ax_4, fill=True, color="C3")
sns.kdeplot(posterior_df["K_I"], ax=ax_4, fill=True, color=palette[2],
↳alpha=0.5)
sns.despine(ax=ax_4)
ax_4.set_xlim(0, 8000)
ax_4.set_ylabel(r"$P(K_{I}|\mathbf{y})$")
ax_4.set_xlabel(r"$K_{I}$")
ax_4.set_xticks([])
ax_4.set_yticks([])

# ax_0 = fig.add_subplot(gs[0, 0])
# sns.despine(ax=ax_0, left=True, bottom=True)
ax_1.text(0.5, 2.25, r"$\mathbf{y}$", transform=ax_1.transAxes, ha='center',
↳fontsize=10, va='center', weight='bold', in_layout=False)
ax_2.text(0.5, 1.05, r"$\mathcal{L}(\mathbf{y}|\theta)$", transform=ax_2.
↳transAxes, fontsize=10, ha='center', va='center', weight='bold',
↳in_layout=False)
ax_3.margins(y=0.2)
ax_3.text(0.5, 1.13, r"$P(\theta|\mathbf{y})$", transform=ax_3.transAxes,
↳ha='center', fontsize=10, va='center', weight='bold', in_layout=True)

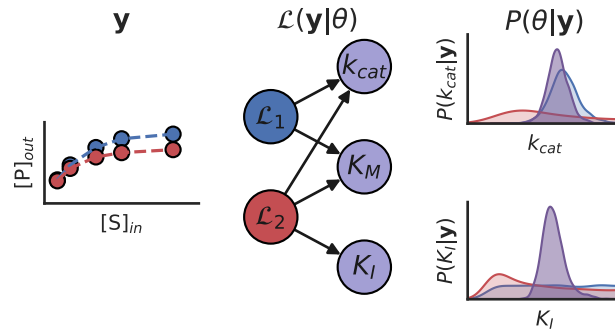
plt.savefig("../figures/fig_toc.svg", dpi=300)
plt.show()

```

/home/mathieu/anaconda3/envs/phd/lib/python3.9/site-packages/numpy/core/\_asarray.py:171: VisibleDeprecationWarning: Creating an

ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.

```
return array(a, dtype, copy=False, order=order, subok=True)
```



[ ]: