The kappa coefficient of agreement

```
import os
if "KERAS_BACKEND" not in os.environ:
    # set this to "torch", "tensorflow", or "jax"
    os.environ["KERAS_BACKEND"] = "jax"

import numpy as np
import bayesflow as bf
import matplotlib.pyplot as plt
```

$$
\begin{aligned}
\alpha, \beta, \gamma &\sim \text{Beta}(1, 1) \\
\pi_a &\leftarrow \alpha\beta \\
\pi_b &\leftarrow \alpha(1-\beta) \\
\pi_c &\leftarrow (1-\alpha)(1-\gamma) \\
\pi_d &\leftarrow (1-\alpha)\gamma \\
\epsilon &\leftarrow \alpha\beta + (1-\alpha)\gamma \\
\psi &(\pi_a + \pi_b)(\pi_a + \pi_c) + (\pi_b + \pi_d)(\pi_c + \pi_d) \\
\kappa &\leftarrow (\epsilon - \psi)/(1-\psi) \\
y &\sim \text{Multinomial}(\pi, n)
\end{aligned}
\tag{1}
$$

Simulator

```
def context():
    return dict(n=np.random.randint(low=150, high=600))

def prior():
    alpha = np.random.beta(a=1, b=1)
    beta  = np.random.beta(a=1, b=1)
```

```
    gamma = np.random.beta(a=1, b=1)

    pi = np.array([
        alpha * beta,
        alpha * (1-beta),
        (1-alpha) * (1-gamma),
        (1-alpha) * gamma
    ])

    epsilon = alpha * beta + (1-alpha) * gamma
    psi = (pi[0] + pi[1]) * (pi[0] + pi[2]) + (pi[1] + pi[3]) * (pi[2] + pi[3])

    kappa = (epsilon - psi)/(1-psi)

    return dict(pi=pi, kappa=kappa)

def likelihood(n, pi):
    y = np.random.multinomial(n=n, pvals=pi)
    return dict(y=y)

simulator = bf.make_simulator([context, prior, likelihood])
```

Approximator

```
adapter = (
    bf.Adapter()
    .constrain("kappa", lower=-1, upper=1)
    .rename("kappa", "inference_variables")
    .rename("y", "inference_conditions")
)
```

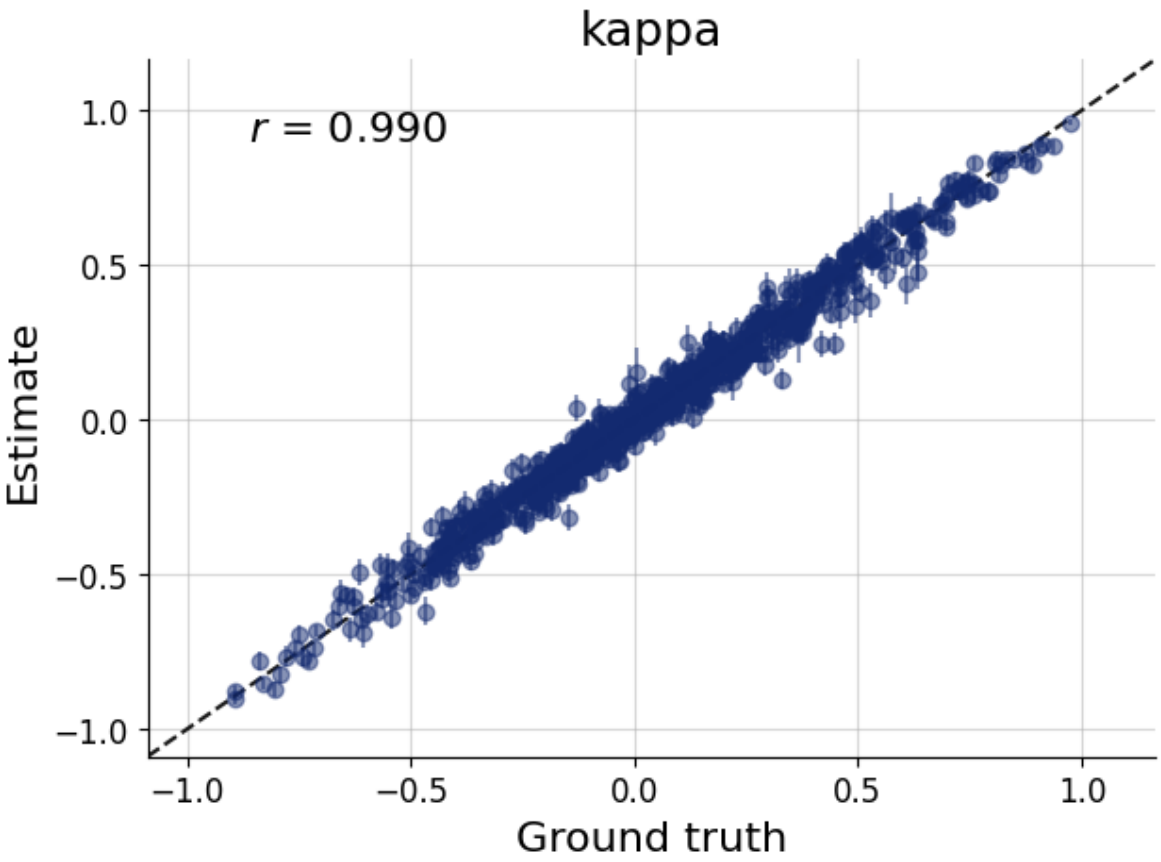
```
workflow = bf.BasicWorkflow(
    simulator=simulator,
    adapter=adapter,
    inference_network=bf.networks.CouplingFlow()
)
```

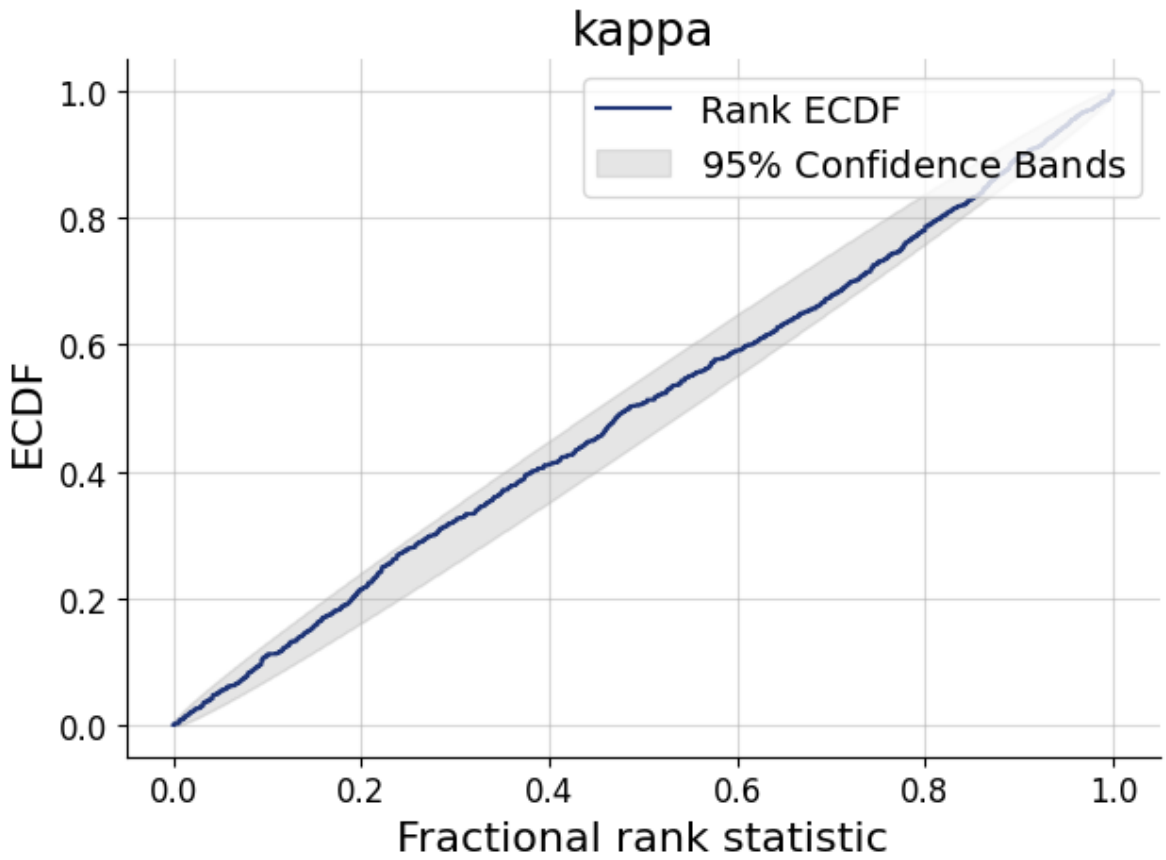
Training

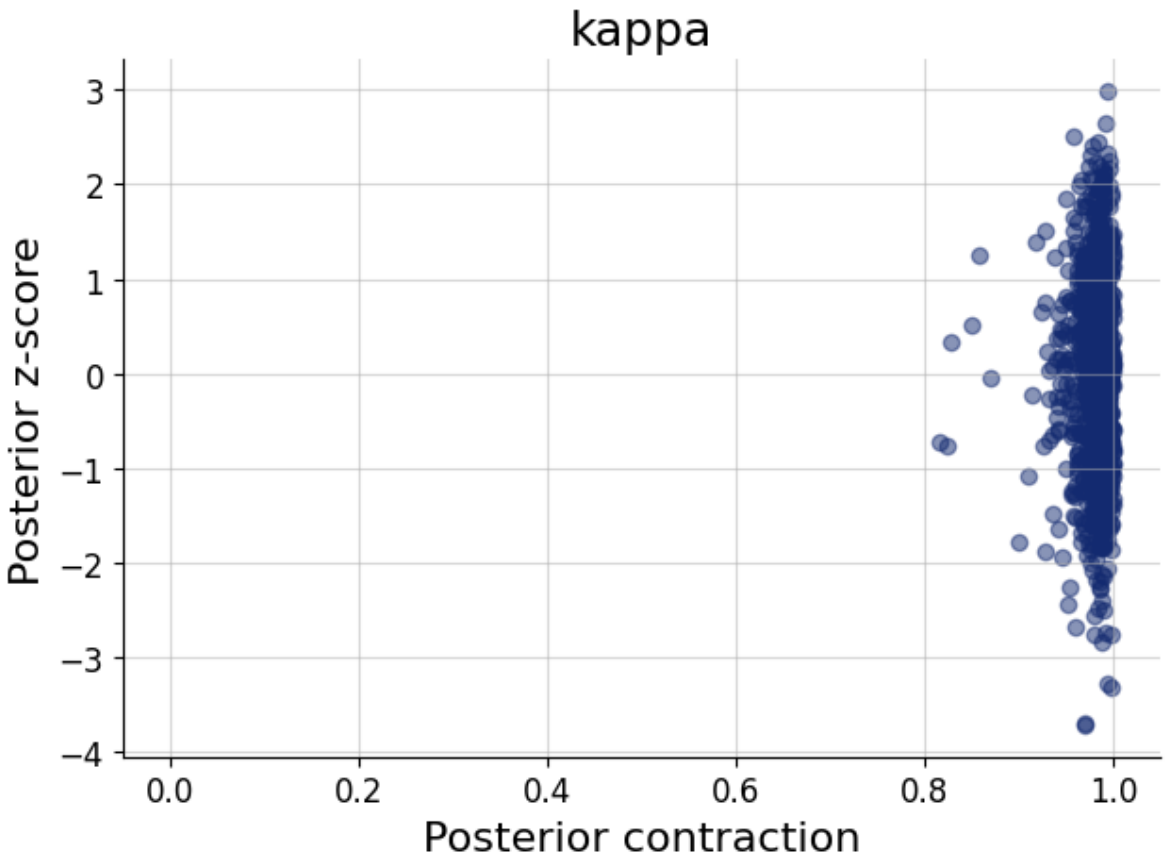
```
history = workflow.fit_online(epochs=50, batch_size=512)
```

Validation

```
test_data = simulator.sample(1000)
figs=workflow.plot_default_diagnostics(test_data=test_data, num_samples=500)
```


kappa
r = 0.990
Estimate
Ground truth
1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0


kappa
Rank ECDF
95% Confidence Bands
ECDF
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Fractional rank statistic



Inference

We will apply the model to three datasets reported by Lee & Wagenmakers (2013, pp. 67–68).

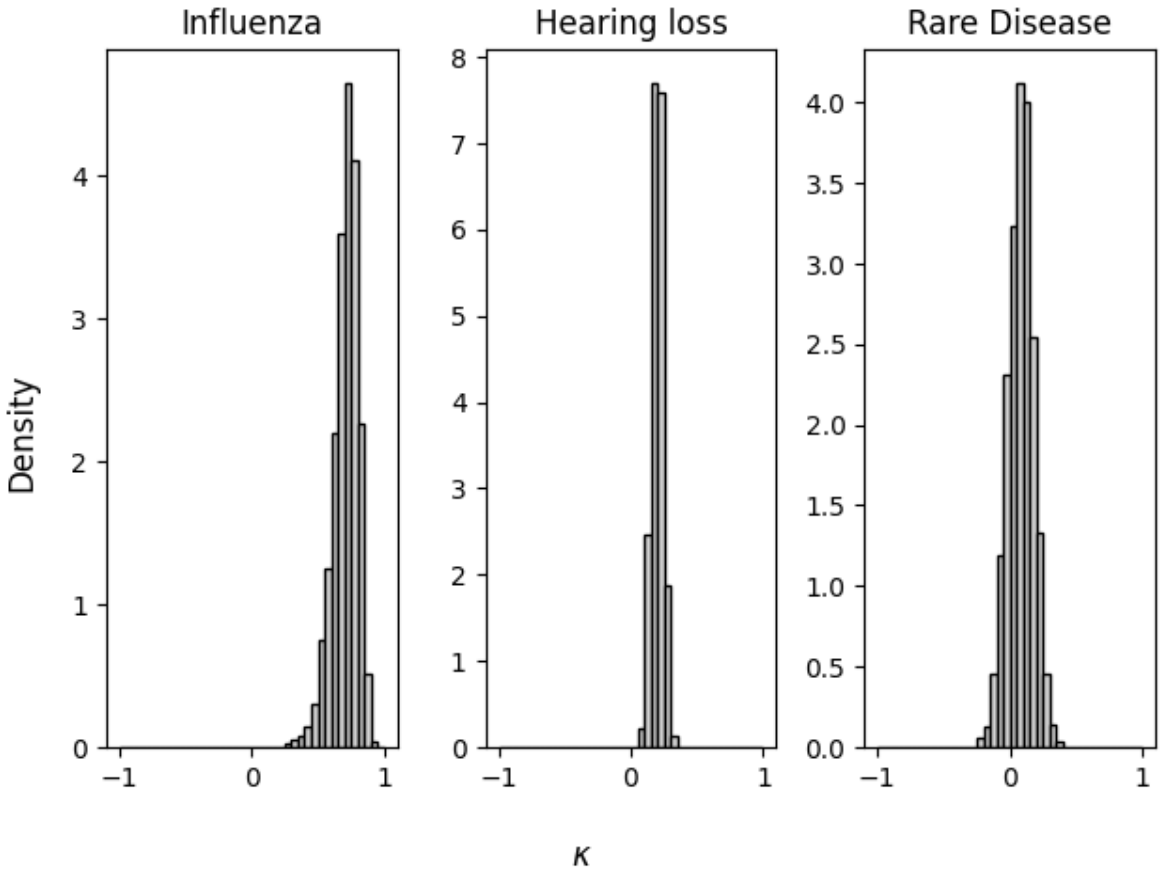
```
inference_data = dict(
    y = np.array(
        [
            [14, 4, 5, 210], # influenza
            [20, 7, 103, 417], # hearing loss
            [0, 0, 13, 157], # rare disease
        ]
    )
)
```

```
samples = workflow.sample(num_samples=2000, conditions=inference_data)
```

```
fig, axs = plt.subplots(ncols=3)
titles = ["Influenza", "Hearing loss", "Rare Disease"]

for i, ax in enumerate(axs):
    ax.set_title(titles[i])
    ax.hist(samples["kappa"][i],
            density=True, color="lightgray", edgecolor="black", bins=np.arange(-1, 1.05, 0.05

fig.supxlabel(r"$\kappa$")
fig.supylabel("Density")
fig.tight_layout()
```



Lee, M. D., & Wagenmakers, E.-J. (2013). *Bayesian Cognitive Modeling: A Practical Course*. Cambridge University Press.