

## Appendix A: Python code for change point analysis

```
import matplotlib.pyplot as plt
import numpy as np
import numba as nb
import pandas as pd
```

```
@nb.njit
def sample_idx(weights):
    """ Sample an index with probability proportional to its weight. """
    weights = weights / np.sum(weights)
    u = np.random.uniform(0, 1)
    partial_sum = weights[0]
    idx = 0
    while u > partial_sum:
        idx += 1
        partial_sum += weights[idx]
    return idx
```

```
@nb.jit(fastmath=True)
def binomial_changepoint_model_samples(
    x1: np.ndarray,
    x2: np.ndarray,
    init_t1: np.float64,
    init_t2: np.float64,
    init_k: np.int64,
    n_iters: np.int64 = 100_000,
    seed: np.int64 = 0,
) -> np.ndarray:
    """
```

Run the Gibbs sampler for the Binomial changepoint model.

This function will run a Gibbs sampler for the binomial changepoint model where the number of occurrences of one variant over time is given by  $x_1$  and the number of occurrences of the alternative variant over the same time frame is given by  $x_2$ .

The Binomial changepoint model assumes that  $X_1 \sim \text{Binom}(n, t_1)$  before the changepoint. That is, for each period of time  $\leq k$ . Here,  $n$  is the total number of occurrences of either variant (i.e.  $n = X_1 + X_2$ ),  $X_1$  is the number of occurrences of one variant (and, therefore,  $X_2$  is the number of occurrences of the alternative variant), and  $k$  is the index at which the change occurred.

The Binomial changepoint model assumes that  $X_2 \sim \text{Binom}(n, t_2)$  after the changepoint. That is, for each period of time  $> k$ .

### Parameters

-----

**x1:** np.ndarray

An array containing, over a given time frame, the number of occurrences of one variant. E.g.  $x_1[0]$  is the number of occurrences of near in 1771,  $x_1[1]$  is the number of occurrences of near in 1772, and so on.

**x2:** np.ndarray

An array containing, over a given time frame, the number of occurrences of the variant that is alternative to the variant which is tracked in  $x_1$ . E.g.  $x_2[0]$  is the number of occurrences of nearly in 1771,  $x_2[1]$  is the number of occurrences of nearly in 1772, and

so on.

`init_t1: np.float64`  
An initial value for the Binomial probability parameter before the changepoint. That is, a value for `t1` at which to start the Gibbs sampler.

`init_t2: np.float64`  
An initial value for the Binomial probability parameter after the changepoint. That is, a value for `t2` at which to start the Gibbs sampler.

`init_k: np.int64`  
An initial value for the index at which the change occurred.

`n_iters: np.int64`  
The number of iterations for which to run the Gibbs sampler.

`seed: np.int64`  
The seed for the random number generator. Ensures reproducibility.

### Returns

```

-----
t1_out: np.ndarray
    The sampled values for t1.
t2_out: np.ndarray
    The sampled values for t2.
k_out: np.ndarray
    The sampled values for k.
"""
n_periods = len(x1)
total_occ = x1 + x2
t1_out = np.empty(n_iters + 1, dtype=np.float64)
t2_out = np.empty(n_iters + 1, dtype=np.float64)
k_out = np.empty(n_iters + 1, dtype=np.int64)
ws = np.empty(n_periods, dtype=np.float64)
t1_out[0], t2_out[0], k_out[0] = init_t1, init_t2, init_k
np.random.seed(seed)
for i in range(n_iters):
    t1, t2, k = t1_out[i], t2_out[i], k_out[i]
    sum_x_before = np.sum(x1[:k + 1])
    sum_occ_before = np.sum(total_occ[:k + 1])
    sum_all_x = np.sum(x1)
    sum_all_occ = np.sum(total_occ)
    t1 = np.random.beta(sum_x_before + 1.0, sum_occ_before - sum_x_before + 1.0)
    t2 = np.random.beta(
        sum_all_x - sum_x_before + 1.0,
        (sum_all_occ - sum_occ_before) - (sum_all_x - sum_x_before) + 1.0
    )
    for j in range(n_periods):
        sum_x_before = np.sum(x1[:j + 1])
        sum_occ_before = np.sum(total_occ[:j + 1])
        log_weight = (
            sum_x_before * (np.log(t1) - np.log(t2)) +
            (sum_occ_before - sum_x_before) * (np.log(1.0 - t1) - np.log(1.0 - t2))
        )
        ws[j] = np.exp(log_weight)
    k = sample_idx(ws)
    t1_out[i + 1], t2_out[i + 1], k_out[i + 1] = t1, t2, k
return t1_out, t2_out, k_out

```

```

data = pd.read_csv('./data.csv')
data['total'] = data['abortion'] + data['miscarriage']

```

```
data['proportion'] = data['abortion'] / data['total']

x1 = data['abortion'].values
x2 = data['miscarriage'].values
init_k = 10
init_date = 1985
before_mask = (data['year'] <= init_date)
after_mask = (data['year'] > init_date)
init_t1 = data.loc[before_mask, 'proportion'].mean()
init_t2 = data.loc[after_mask, 'proportion'].mean()

out = binomial_changepoint_model_samples(x1, x2, init_t1, init_t2, init_k, 100_000, 12345)

years = data['year'].values
idxs, counts = np.unique(out[-1], return_counts=True)

plt.bar(years[idxs], counts / counts.sum())
plt.hist(out[0], bins=500)
plt.hist(out[1], bins=500)
```