Event Based Models for Disease Progression

Hongtao Hao & Joseph Austerweil

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1 Introduction

You can also read the material in PDF.

Event-based Model (EBM) is used to model the order of degenerative diseases. In another word, we want to estimate the order in which different biological factors ("biomarkers") get affected by a specific disease. The order is categorized by multiple **stages** in the disease progression.

For instance, Alzheimer may have the following stages:

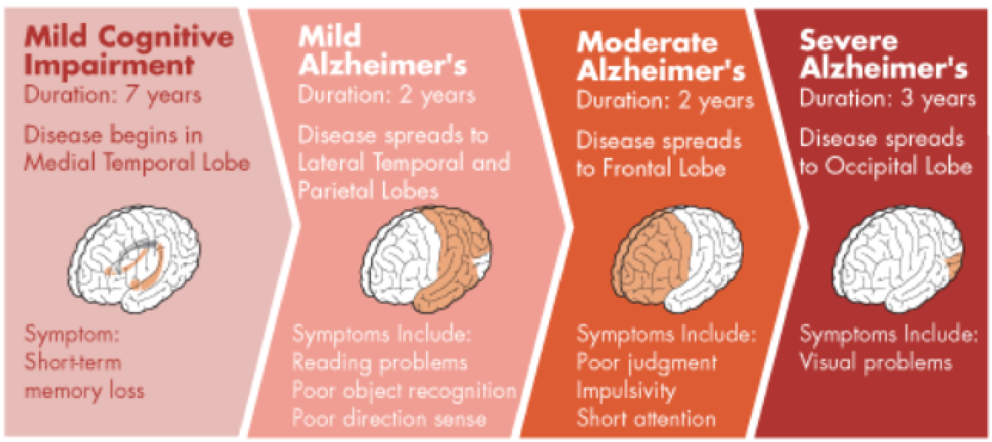

Figure 1.1: Alzheimer Disease Progression (Credit: https://preventad.com/alzheimers-disease/)

We estimate this order based on the biomarker data from patients' visits. These data are typically results of neuropsych (e.g., MMSE) and/or biological examiations (e.g., blood pressure). Visits data can be longitudinal and/or cross-sectional, i.e., single visits from a cohort of patients.

Knowing the disease progression is important because it helps prevent and hopefully cure the disease. It also helps health professionals prepare for the disease's further development.

We have several assumptions in EBM:

- The disease is irreversible (i.e., a patient cannot go from stage 2 to stage 1)
- The order in which different biomarkers get affected by the disease is the same across all patients.

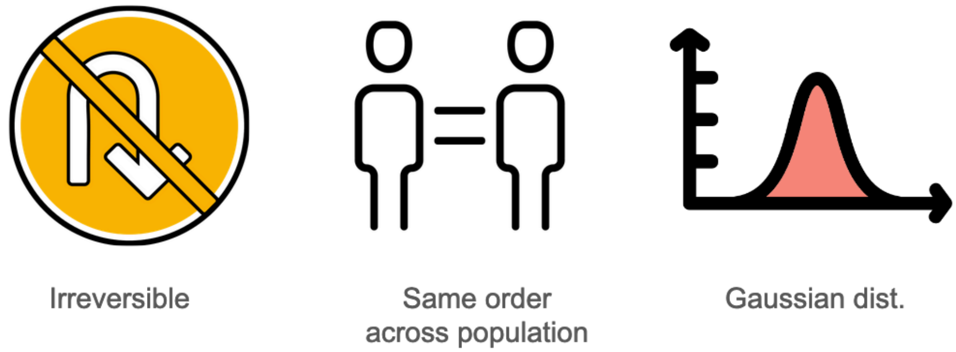

Figure 1.2: Assumptions of EBM

- Biomarker data can be approximated by a Gaussian distribution.

> **Pay Attention**
>
> The third assumption, i.e., Gaussian approximation, isn't always hold. However, for the purpose of our current method, we assume this is true. There are other methods that do not assume Gaussian distributions, for example, KDE EBM, against which we will compare results with later in our report.

This book contains chapters that explain step by step how we use the event-based model to estimate the order of disease progression based on cross-sectional patients' biomarker data.

2 EBM as A Generative Model

We can use EBM to generate synthetic biomarker data if we know:

- The order (S) in which different biomarkers get affected by the disease.
- Parameters (i.e., mean and standard deviation) of biomarkers' distribution when they are affected (θ) and not affected (ϕ) by the disease.
- Stages (k_j) that each participant is in.

Data we can generate looks like this:

	participant	biomarker	measurement	k_j	S_n	affected_or_not	Diseased
0	67	HIP-FCI	22.478591	2	1	affected	True
1	67	HIP-GMI	-5.102497	2	3	not_affected	True
2	67	FUS-FCI	322.304772	2	5	not_affected	True
3	67	PCC-FCI	-5.690280	2	2	affected	True
4	67	FUS-GMI	6.345347	2	4	not_affected	True

Figure 2.1: Sample Data

This data is from a single participant.

As we mentioned above, to generate this data, we need to know:

- S, i.e., the order of biomarkers. In the above example, S is HIP-FCI, PCC-FCI, HIP-GMI, FUS-GMI, FUS-FCI.
- $\mathcal{N}(\theta_\mu, \theta_\sigma)$ and $\mathcal{N}(\phi_\mu, \phi_\sigma)$ for each of the five biomarkers, which are known but not shown directly here in the dataset.
- k_j, which is 2 in the above example.

We explain how this data is constructed in the following, column by column.

First, the `participant` id is 67. The `biomarker` indicates each of the five biomarkers examined and measured. The `measurement` is the biomarkers' measurement. `k_j` is the participant's stage. If this stage is above 0, it means `Diseased = True`. `S_n` indicates the n-th rank in the order. If `k_j < S_n`, it means the participant's stage hasn't reached that biomarker's rank; therefore, this biomarker is `not affected`. If `k_j >= S_n`, then this biomarker is `affected`.

If a biomarker is `affected`, then its measurement comes from $\mathcal{N}(\theta_\mu, \theta_\sigma)$ of that biomarker; if `not_affected`, $\mathcal{N}(\phi_\mu, \phi_\sigma)$.

2.1 Generative Process

The generative process of biomarker measurements can be described as:

$$X_{nj} \mid S, k_j, \theta_n, \phi_n \sim I(z_j = 1)\Big[I(S(n) \leq k_j)\, p(X_{nj} \mid \theta_n) + I(S(n) > k_j)\, p(X_{nj} \mid \phi_n)\Big] + \big(1 - I(z_j = 1)\big)\, p(X_{nj} \mid \phi \tag{2.1}$$

This model says that given that we know S, k_j, θ_n, and ϕ_n, we can draw the biomarker measurement from a distribution.

$S \sim \text{UniformPermutation}(\cdot)$

S follows a distribution of uniform permutation. That means the ordering of biomarkers is random.

$k_j \sim \text{DiscreteUniform}(N)$

k_j follows a discrete uniform distribution, which means a participant is equally likely to fall in a progression stage (e.g., from 0 to 5, where 0 indicate this participant is healthy.)

2.2 Graphical Explanation

In the following, we explain the generative model in three different scenarios using graphical models: (1) All participants are healthy; (2) Both healthy and diseased participants, but all biomarkers are affected among diseased people; (3) Both healthy and diseased participants, but we do not whether biomarkers are affected or not among patients.

2.2.1 Scenario 1

If all participants are healthy:

$$X_{nj} \sim p(X_{nj} \mid \phi_n) \tag{2.2}$$

Where

X_{nj} indicates the measurement of biomarker n in participant j.

ϕ_n represents $\mathcal{N}(\phi_\mu, \phi_\sigma)$ for biomarker n.

The graphical model would look like:

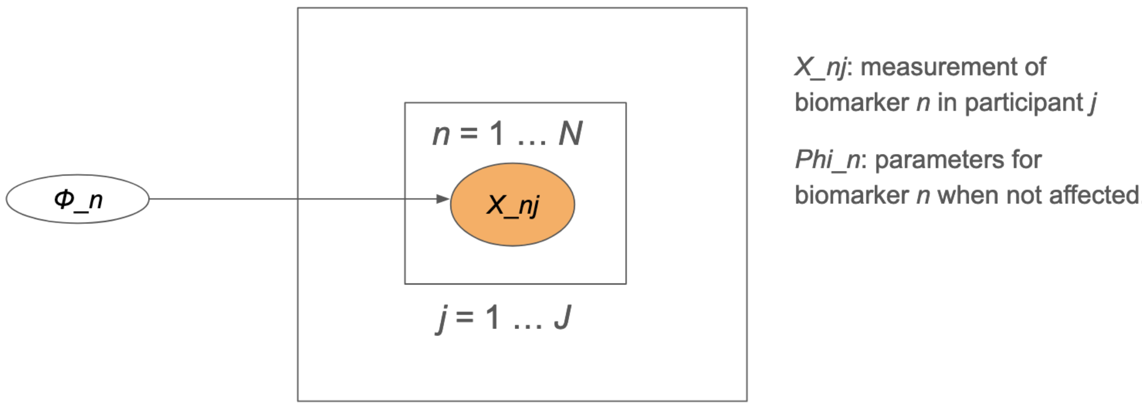

Figure 2.2: Graphical Model of Scenario 1

2.2.2 Scenario 2

If we have oth diseased and healthy participants, and all biomarkers are affected among diseased participants.

$$X_{nj} \sim I(z_j == 1)p(X_{nj} \mid \theta_n) + (1 - I(z_j == 1))p(X_{nj} \mid \phi_n) \tag{2.3}$$

Where:

$z_j = 1$ indicates this participant is diseased and $z_j = 1$ represents a healthy participant.

$I(True) = 1$ and $I(False) = 0$.

θ_n represents $\mathcal{N}(\theta_\mu, \theta_\sigma)$ for biomarker n.

The graphical model would look like:

2.2.3 Scenario 3

If we have both healthy and diseased participants, but we do not whether biomarkers are affected or not among patients, see Equation 2.1.

This is the model in usual cases.

The graphical model looks like:

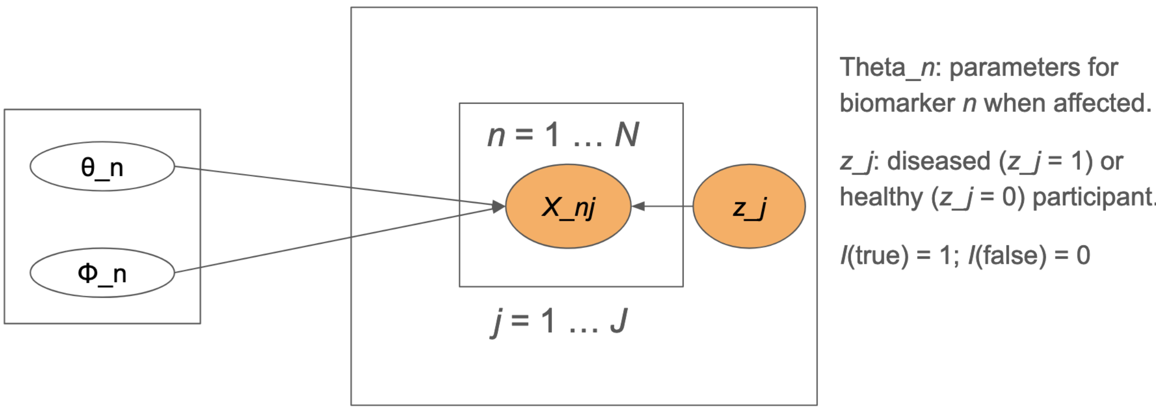

Figure 2.3: Graphical Model of Scenario 2

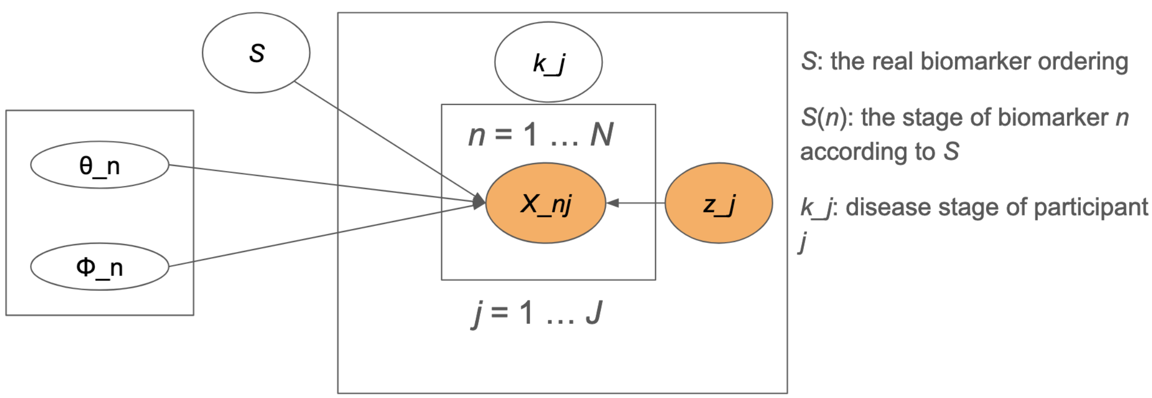

Figure 2.4: Graphical Model of Scenario 3

3 Calculate the Likelihood of Biomarker Measurements

Suppose we have a participant's data, for example, Figure 2.1. Now, the question is:

> What is the likelihood of this participant having this sequence of biomarker data, given that we know S, θ, ϕ.

In the following, we explain how to calculate this likelihood in two scenartios: (1) known k_j and (2) unknown k_j.

3.1 Known k_j

$$p(X_j|S, z_j = 1, k_j) = \underbrace{\prod_{i=1}^{k_j} p(X_{S(i)j} \mid \theta_{S(i)})}_{\text{Affected biomarker likelihood}} \underbrace{\prod_{i=k_j+1}^{N} p(X_{S(i)j} \mid \phi_{S(i)})}_{\text{Non-affected biomarker likelihood}} \tag{3.1}$$

This equation compuates the likelihood of the observed biomarker data of a specific participant, given that we know the disease stage this patient is at (k_j).

- S is an **orded array** of biomarkers that are affected by the disease, for example, $[b, a, d, c]$. This means that biomarker b is affected at stage 1. At stage 2, biomarker b and a will be affected.
- $S(i)$ is the i^{th} biomarker according to S. For example S_1 will be biomarker b.
- k_j indicates the stage the patient is at, for example, $k_j = 2$. This means that the disease has effected biomarker a and b. Biomarker c and d have not been affected yet.
- $\theta_{S(i)}$ is the parameters for the probability density function (PDF) of observed value of biomarker $S(i)$ when this biomarker has been affected by the disease. Let's assume this distribution is a Gaussian distribution with means of $[45, 50, 55, 60]$ and a standard deviation of 5 for biomarker b, a, d, and c.

- $\phi_{S(i)}$ is the parameters for the probability density function (PDF) of observed value of biomarker $S(i)$ when this biomarker has **NOT** been affected by the disease. Let's assume this distribution is a Gaussian distribution with means of $[25, 30, 35, 40]$ and a standard deviation of 3 for biomarker b, a, d, and c.
- X_j is an array representing the patient's observed data for all biomarker. Assume the data is $[77, 45, 53, 90]$ for biomarker b, a, d, and c.

We assume that the patient is at stage 2 of this disease; hence $k_j = 2$.

Next, we are going to calculate $p(X_j|S, z_j = 1, k_j)$:

When $i = 1$, we have $S_{(i)} = b$ and $X_{S_{(i)}} = X_b = 45$. So

$$p(X_{S_{(i)}}|\theta_{S(i)}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{X_b-\mu}{\sigma}\right)^2}$$

Because $k_j = 2$, so biomarker b and a are affected. We should use the distribution of θ_b; therefore, we should plug in $\mu = 45, \sigma = 5$ in the above equation.

We can do the same for $i = 2$, 3, and 4.

So

$$p(X_j|S, k_j = 2) = p(X_b|\theta_b) \times p(X_a|\theta_a) \times p(X_d|\phi_d) \times p(X_c|\phi_c)$$

The above is the likelihood of the given biomarker data when $k_j = 2$.

Note that $p(X_b|\theta_b)$ is probability density, a value of a probability density function at a specific point; so it is not a probability itself.

Multiplying multiple probability densities will give us a likelihood.

3.2 Unknown k_j

$$P(X_j|S) = \sum_{k_j=0}^{N} P(k_j)p(X_j \mid S, k_j) \tag{3.2}$$

Suppose we have the same information above, except that we do not know at which disease stage the patient is, i.e., we do not know k_j. We have the observed biomarker data: $X_j = [77, 45, 53, 90]$. And I wonder: what is the likelihood of seeing this specific ovserved data?

We assume that all five stages (including $k_j = 0$) are equally likely.

We do not know k_j, so the best option is to calculate the "average" likelihood of all the biomarker data.

Based on Equation 3.1, we can calculate the following:

$L_1 = p(X_j|S, k_j = 1)$

$L_2 = p(X_j|S, k_j = 2)$

$L_3 = p(X_j|S, k_j = 3)$

$L_4 = p(X_j|S, k_j = 4)$

If this participant is healthy, then we know $k_j = 0$, therefore:

$$L = L_0 = p(X_j|S, k_j = 0) = p(X_b|\phi_b) \times p(X_a|\phi_a) \times p(X_d|\phi_d) \times p(X_c|\phi_c)$$

If this participant is diseased but we do not know the actual k_j, we can estimate it this way

$$L_1 = p(X_j|S, k_j = 1) = p(X_b|\theta_b) \times p(X_a|\phi_a) \times p(X_d|\phi_d) \times p(X_c|\phi_c)$$

$$L_2 = p(X_j|S, k_j = 2) = p(X_b|\theta_b) \times p(X_a|\theta_a) \times p(X_d|\phi_d) \times p(X_c|\phi_c)$$

$$L_3 = p(X_j|S, k_j = 3) = p(X_b|\theta_b) \times p(X_a|\theta_a) \times p(X_d|\theta_d) \times p(X_c|\phi_c)$$

$$L_4 = p(X_j|S, k_j = 4) = p(X_b|\theta_b) \times p(X_a|\theta_a) \times p(X_d|\theta_d) \times p(X_c|\theta_c)$$

$P(k_j)$ is the prior likelihood of being at stage k. **Event based models assume a uniform prior on** k_j. Therefore:

$P(X_j|z_j = 1, S) = \frac{1}{4}(L_1 + L_2 + L_3 + L_4)$

Tip

When this participant is diseased but we do not know the actual stage of this participant, the above method is useful also because it hints at the relative likelihood of each possible stage. For example, if L2 is much larger than L1, L3, and L4, then we know this participant is most likely to be at stage 2.

3.3 Extension

If we are more interested in the likelihood of a whole dataset consisting of all participants, we multiply all participants' likelihood: $L = L_{P_1} \times L_{P_2} \times L_{P_3} ... \times L_{P_j}$. Because this number tends to be very large, we take the natural log of L, i.e., $\ln(L)$.

4 Generate Synthetic Data

In this chapter, we talk about how we generate the synthetic data of participants' biomarker measurements. These data are used to test our algorithms.

4.1 Obtain Estimated Distribution Parameters

In Chapter 2, we mentioned that EBM can be used as a generative model and we need to know S, θ, ϕ and k_j.

First, we obtained S, θ, ϕ from Chen et al. (2016):

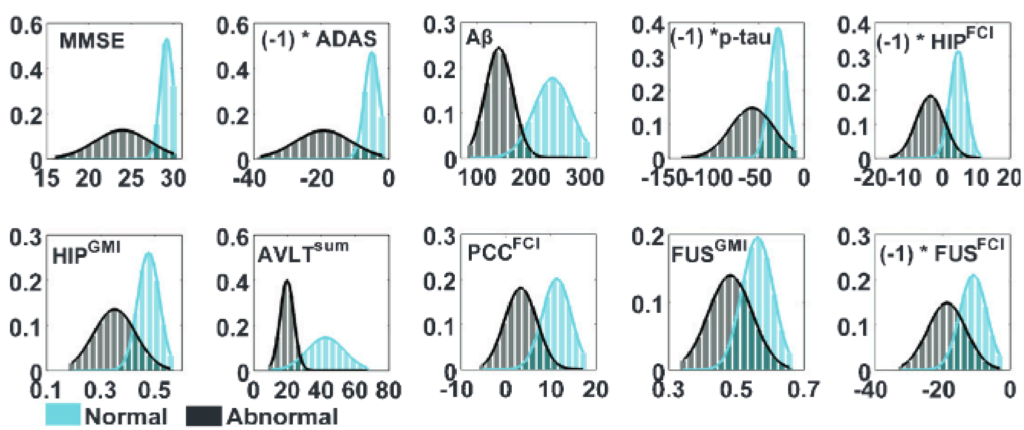

Fig. 1. Probability distributions of normal (cyan) and abnormal (black) events measured by biomarkers from the AD and CN populations. The y-axis denotes the proportion of subjects, while the x-axis indicates the detected value of each biomarker measurement. The (−1) is employed to reverse the signs of the biomarker, indicating the left distribution is an event that occurred and the right distribution is an event that did not occur.

Figure 4.1: Theta and Phi from Chen's Paper

This is our estimation:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import json
```

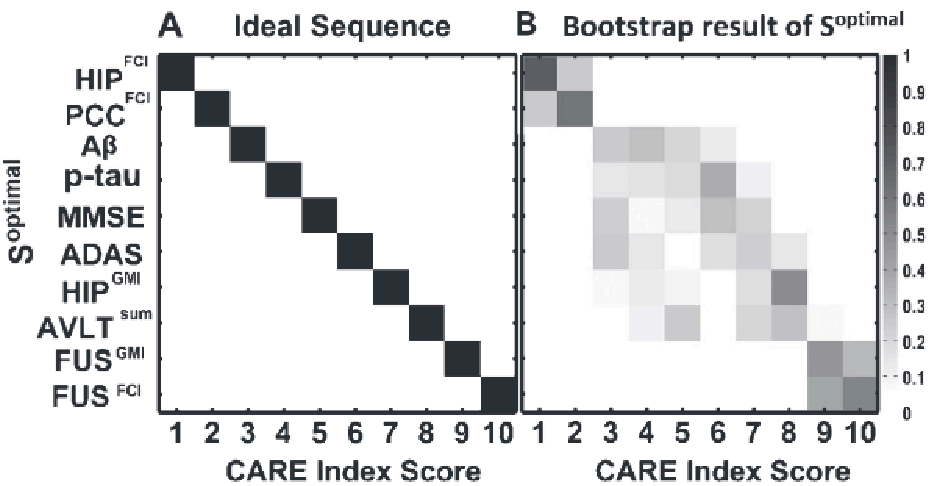

Fig. 2. Optimal temporal order, $S^{optimal}$, of the 10 AD biomarkers estimated by the EBP model. A) The y-axis shows the $S^{optimal}$ and the x-axis shows the CARE index score at which the corresponding event occurred. B) Bootstrap cross-validation of the $S^{optimal}$. Each entry in the matrix represents the proportion of the $S^{optimal}$ during 500 bootstrap samples. The proportion values range from 0 to 1 and correspond to color, from white to black. The CARE index scores with their corresponding biomarkers follow: 1, increased HIP^{FCI}; 2, decreased PCC^{FCI}; 3, decreased Aβ concentration; 4, increased p-tau concentration; 5, decreased MMSE score; 6, increased ADAS score; 7, decreased HIP^{GMI}; 8, decreased AVLT score; 9, decreased FUS^{GMI}; 10, increased FUS^{FCI}.

Figure 4.2: S from Chen's Paper

```
import scipy.stats as stats
from typing import List, Optional, Tuple, Dict
import os
import seaborn as sns
import altair as alt
```

```
all_ten_biomarker_names = np.array([
    'MMSE', 'ADAS', 'AB', 'P-Tau', 'HIP-FCI',
    'HIP-GMI', 'AVLT-Sum', 'PCC-FCI', 'FUS-GMI', 'FUS-FCI'])
# in the order above
# cyan, normal
phi_means = [28, -6, 250, -25, 5, 0.4, 40, 12, 0.6, -10]
# black, abnormal
theta_means = [22, -20, 150, -50, -5, 0.3, 20, 5, 0.5, -20]
# cyan, normal
phi_std_times_three = [2, 4, 150, 50, 5, 0.7, 45, 12, 0.2, 10]
phi_stds = [std_dev/3 for std_dev in phi_std_times_three]
# black, abnormal
theta_std_times_three = [8, 12, 50, 100, 20, 1, 20, 10, 0.2, 18]
theta_stds = [std_dev/3 for std_dev in theta_std_times_three]
```

```python
# to get the real_theta_phi means and stds
hashmap_of_dicts = {}
for i, biomarker in enumerate(all_ten_biomarker_names):
    dic = {}
    # dic = {"biomarker": biomarker}
    dic['theta_mean'] = theta_means[i]
    dic['theta_std'] = theta_stds[i]
    dic['phi_mean'] = phi_means[i]
    dic['phi_std'] = phi_stds[i]
    hashmap_of_dicts[biomarker] = dic
hashmap_of_dicts

real_theta_phi = pd.DataFrame(hashmap_of_dicts).transpose().reset_index(names=['biomarker'])
real_theta_phi
```

	biomarker	theta_mean	theta_std	phi_mean	phi_std
0	MMSE	22.0	2.666667	28.0	0.666667
1	ADAS	-20.0	4.000000	-6.0	1.333333
2	AB	150.0	16.666667	250.0	50.000000
3	P-Tau	-50.0	33.333333	-25.0	16.666667
4	HIP-FCI	-5.0	6.666667	5.0	1.666667
5	HIP-GMI	0.3	0.333333	0.4	0.233333
6	AVLT-Sum	20.0	6.666667	40.0	15.000000
7	PCC-FCI	5.0	3.333333	12.0	4.000000
8	FUS-GMI	0.5	0.066667	0.6	0.066667
9	FUS-FCI	-20.0	6.000000	-10.0	3.333333

Store the parameters to a `JSON` file:

```python
with open('files/real_theta_phi.json', 'w') as fp:
    json.dump(hashmap_of_dicts, fp)
```

```python
biomarkers = all_ten_biomarker_names
n_biomarkers = len(biomarkers)

def plot_distribution_pair(ax, mu1, sigma1, mu2, sigma2, title):
    """mu1, sigma1: theta
    mu2, sigma2: phi
    """
```

```python
    xmin = min(mu1 - 4*sigma1, mu2-4*sigma2)
    xmax = max(mu1 + 4*sigma1, mu2 + 4*sigma2)
    x = np.linspace(xmin, xmax, 1000)
    y1 = stats.norm.pdf(x, loc = mu1, scale = sigma1)
    y2 = stats.norm.pdf(x, loc = mu2, scale = sigma2)
    ax.plot(x, y1, label = "Abnormal", color = "black")
    ax.plot(x, y2, label = "Normal", color = "cyan")
    ax.fill_between(x, y1, alpha = 0.3, color = "black")
    ax.fill_between(x, y2, alpha = 0.3, color = "cyan")
    ax.set_title(title)
    ax.legend()

fig, axes = plt.subplots(2, n_biomarkers//2, figsize=(20, 10))
for i, biomarker in enumerate(biomarkers):
    ax = axes.flatten()[i]
    mu1, sigma1, mu2, sigma2 = real_theta_phi[
        real_theta_phi.biomarker == biomarker].reset_index().iloc[0, :][2:].values
    plot_distribution_pair(
        ax, mu1, sigma1, mu2, sigma2, title = biomarker)
```

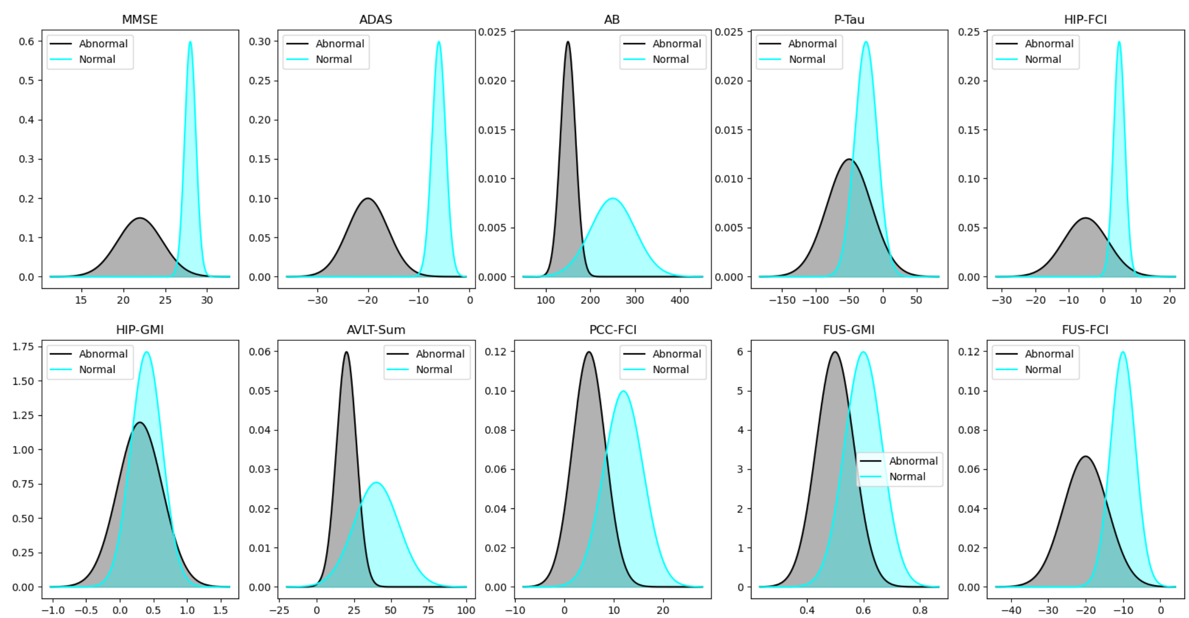

Figure 4.3: evaluate theta and phi estimations

You can compare this to Figure 4.1.

4.2 The Generating Process

In the following, we explain our data generation process.

We have the following parameters:

J: Number of participants.

R: The percentage of healthy participants.

M: Number of datasets per combination of j and r.

We set these parameters:

```
js = [50, 200, 500]
rs = [0.1, 0.25, 0.5, 0.75, 0.9]
num_of_datasets_per_combination = 50
```

So, there will be $3 \times 5 \times 50 = 750$ datasets to be generated.

We define our `generate_data_from_ebm` function:

```
def generate_data_from_ebm(
    n_participants: int,
    S_ordering: List[str],
    real_theta_phi_file: str,
    healthy_ratio: float,
    output_dir: str,
    m,  # combstr_m
    seed: Optional[int] = 0
) -> pd.DataFrame:
    """
    Simulate an Event-Based Model (EBM) for disease progression.

    Args:
    n_participants (int): Number of participants.
    S_ordering (List[str]): Biomarker names ordered according to the order
        in which each of them get affected by the disease.
    real_theta_phi_file (str): Directory of a JSON file which contains
        theta and phi values for all biomarkers.
        See real_theta_phi.json for example format.
    output_dir (str): Directory where output files will be saved.
    healthy_ratio (float): Proportion of healthy participants out of n_participants.
    seed (Optional[int]): Seed for the random number generator for reproducibility.
```

```
    Returns:
    pd.DataFrame: A DataFrame with columns 'participant', "biomarker", 'measurement',
        'diseased'.
    """
    # Parameter validation
    assert n_participants > 0, "Number of participants must be greater than 0."
    assert 0 <= healthy_ratio <= 1, "Healthy ratio must be between 0 and 1."

    # Set the seed for numpy's random number generator
    rng = np.random.default_rng(seed)

    # Load theta and phi values from the JSON file
    try:
        with open(real_theta_phi_file) as f:
            real_theta_phi = json.load(f)
    except FileNotFoundError:
        raise FileNotFoundError(f"File {real_theta_phi} not fount")
    except json.JSONDecodeError:
        raise ValueError(
            f"File {real_theta_phi_file} is not a valid JSON file.")

    n_biomarkers = len(S_ordering)
    n_stages = n_biomarkers + 1

    n_healthy = int(n_participants * healthy_ratio)
    n_diseased = int(n_participants - n_healthy)

    # Generate disease stages
    kjs = np.concatenate((np.zeros(n_healthy, dtype=int),
                          rng.integers(1, n_stages, n_diseased)))
    # shuffle so that it's not 0s first and then disease stages bur all random
    rng.shuffle(kjs)

    # Initiate biomarker measurement matrix (J participants x N biomarkers) with None
    X = np.full((n_participants, n_biomarkers), None, dtype=object)

    # Create distributions for each biomarker
    theta_dist = {biomarker: stats.norm(
        real_theta_phi[biomarker]['theta_mean'],
        real_theta_phi[biomarker]['theta_std']
    ) for biomarker in S_ordering}
```

```python
phi_dist = {biomarker: stats.norm(
    real_theta_phi[biomarker]['phi_mean'],
    real_theta_phi[biomarker]['phi_std']
) for biomarker in S_ordering}

# Populate the matrix with biomarker measurements
for j in range(n_participants):
    for n, biomarker in enumerate(S_ordering):
        # because for each j, we generate X[j, n] in the order of S_ordering,
        # the final dataset will have this ordering as well.
        k_j = kjs[j]
        S_n = n + 1

        # Assign biomarker values based on the participant's disease stage
        # affected, or not_affected, is regarding the biomarker, not the participant
        if k_j >= 1:
            if k_j >= S_n:
                # rvs() is affected by np.random()
                X[j, n] = (
                    j, biomarker, theta_dist[biomarker].rvs(random_state=rng), k_j, S_n,
            else:
                X[j, n] = (j, biomarker, phi_dist[biomarker].rvs(random_state=rng),
                           k_j, S_n, 'not_affected')
        # if the participant is healthy
        else:
            X[j, n] = (j, biomarker, phi_dist[biomarker].rvs(random_state=rng),
                       k_j, S_n, 'not_affected')

df = pd.DataFrame(X, columns=S_ordering)
# make this dataframe wide to long
df_long = df.melt(var_name="Biomarker", value_name="Value")
data = df_long['Value'].apply(pd.Series)
data.columns = ['participant', "biomarker",
                'measurement', 'k_j', 'S_n', 'affected_or_not']

# biomarker_name_change_dic = dict(
#     zip(S_ordering, range(1, n_biomarkers + 1)))
data['diseased'] = data.apply(lambda row: row.k_j > 0, axis=1)
# data.drop(['k_j', 'S_n', 'affected_or_not'], axis=1, inplace=True)
# data['biomarker'] = data.apply(
#     lambda row: f"{row.biomarker} ({biomarker_name_change_dic[row.biomarker]})", axis=
```

```
    if not os.path.exists(output_dir):
        os.makedirs(output_dir)

    filename = f"{int(healthy_ratio*n_participants)}|{n_participants}_{m}"
    data.to_csv(f'{output_dir}/{filename}.csv', index=False)
    # print("Data generation done! Output saved to:", filename)
    return data
```

```
S_ordering = np.array([
    'HIP-FCI', 'PCC-FCI', 'AB', 'P-Tau', 'MMSE', 'ADAS',
    'HIP-GMI', 'AVLT-Sum', 'FUS-GMI', 'FUS-FCI'
])

# where the generated data will be saved
output_dir = 'data'

# We run the following only once; once the data is generated, we no longer run it
# We still show the codes to present our generation process
torun = False
```

```
if torun:
    real_theta_phi_file = 'files/real_theta_phi.json'
    for j in js:
        for r in rs:
            for m in range(0, num_of_datasets_per_combination):
                generate_data_from_ebm(
                    n_participants=j,
                    S_ordering=S_ordering,
                    real_theta_phi_file=real_theta_phi_file,
                    healthy_ratio=r,
                    output_dir=output_dir,
                    m=m,
                    seed = int(j*10 + (r * 100) + m),
                )
        print(f'Done for J={j}')
```

4.3 Visualize Synthetic Data

Above, we have generated 750 datasets, named in the fashion of `150|200_3`, which means the third dataset when $j = 200$ and $r = 0.75$.

Next, we try to visualize this dataset.

```
df = pd.read_csv(f"{output_dir}/150|200_3.csv")
df.head()
```

	participant	biomarker	measurement	k_j	S_n	affected_or_not	diseased
0	0	HIP-FCI	3.135981	0	1	not_affected	False
1	1	HIP-FCI	12.593704	2	1	affected	True
2	2	HIP-FCI	6.220776	0	1	not_affected	False
3	3	HIP-FCI	3.545100	0	1	not_affected	False
4	4	HIP-FCI	3.966541	0	1	not_affected	False

```
df.shape
```

```
(2000, 7)
```

This dataset has 2000 rows because we have 200 participants and 10 biomarkers.

4.3.1 Distribution of all biomarker values

```
alt.renderers.enable('png')
alt.Chart(df).transform_density(
    'measurement',
    as_=['measurement', 'Density'],
    groupby=['biomarker']
).mark_area().encode(
    x="measurement:Q",
    y="Density:Q",
    facet = alt.Facet(
        "biomarker:N",
        columns = 5
    ),
    color=alt.Color(
        'biomarker:N'
    )
).properties(
    width= 100,
    height = 180,
```

```
).properties(
    title='Distribution of biomarker measurments'
)
```

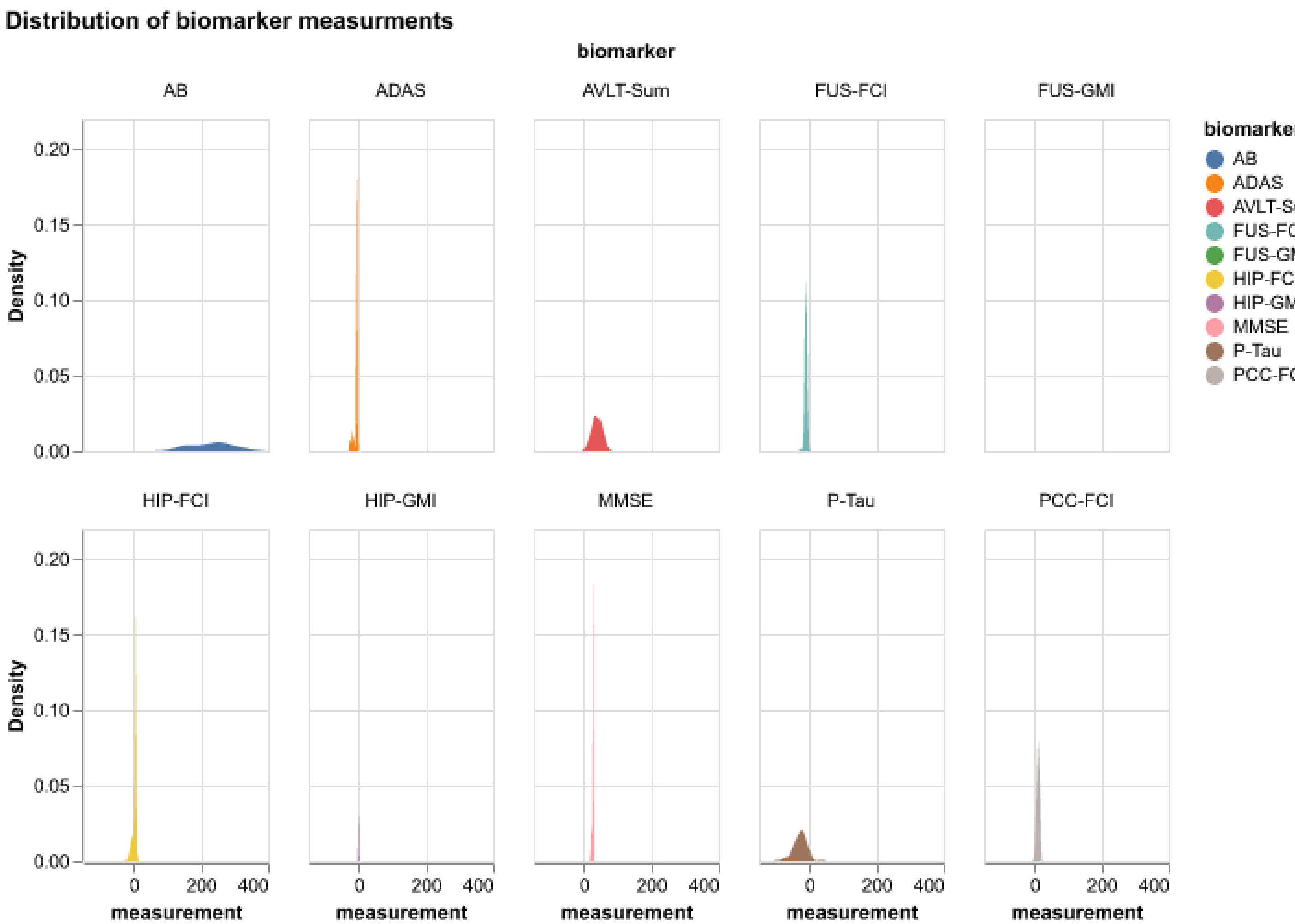

Figure 4.4: Distribution of biomarker measurments

4.3.2 Distribution of A Specific Biomarker

```
idx = 1
biomarkers = df.biomarker.unique()
bio_data = df[df.biomarker==biomarkers[idx]]
```

```
alt.Chart(bio_data).transform_density(
    'measurement',
    as_=['measurement', 'Density'],
    groupby=['affected_or_not']
).mark_area().encode(
    x="measurement:Q",
    y="Density:Q",
    facet = alt.Facet(
        "affected_or_not:N",
    ),
    color=alt.Color(
        'affected_or_not:N'
    )
).properties(
    width= 240,
    height = 200,
).properties(
    title=f'Distribution of {biomarker} measurements'
)
```

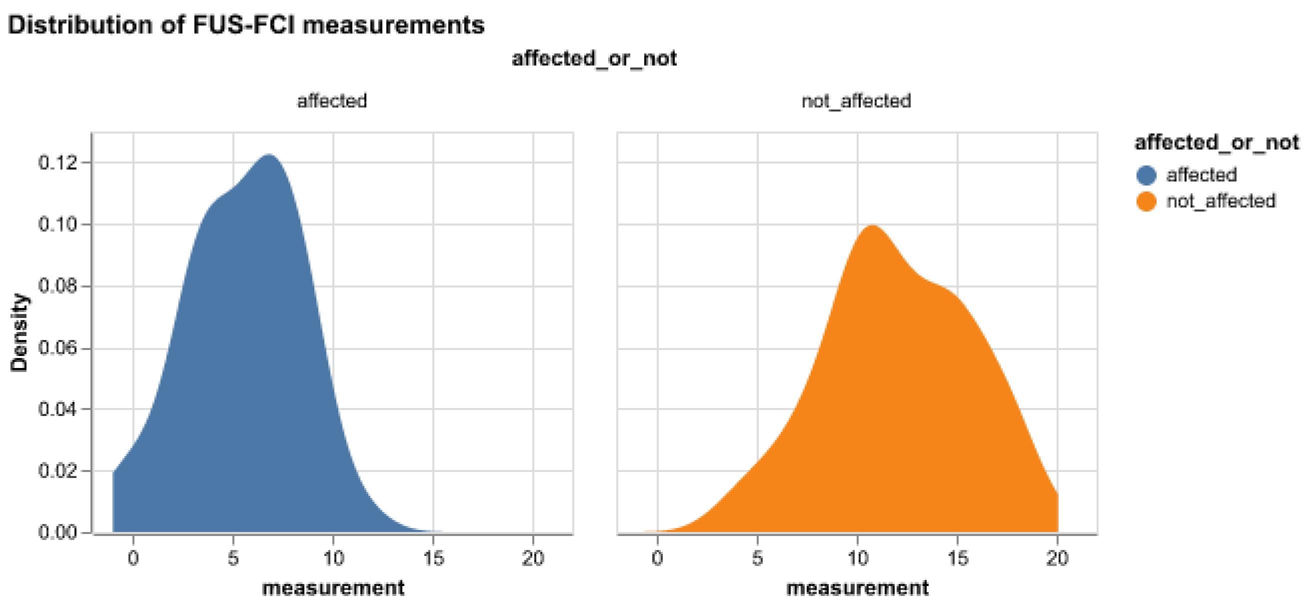

Figure 4.5: Distribution of HIP-FCI measurements, compring bewteen affected and non-affected group

4.3.3 Looking into A Specific Participant

```
pidx = 1
p_data = df[df.participant == pidx]
p_data
```

	participant	biomarker	measurement	k_j	S_n	affected_or_not	diseased
1	1	HIP-FCI	12.593704	2	1	affected	True
201	1	PCC-FCI	7.164017	2	2	affected	True
401	1	AB	182.033823	2	3	not_affected	True
601	1	P-Tau	-25.345325	2	4	not_affected	True
801	1	MMSE	27.600823	2	5	not_affected	True
1001	1	ADAS	-4.920415	2	6	not_affected	True
1201	1	HIP-GMI	0.099052	2	7	not_affected	True
1401	1	AVLT-Sum	30.270797	2	8	not_affected	True
1601	1	FUS-GMI	0.658954	2	9	not_affected	True
1801	1	FUS-FCI	-11.701559	2	10	not_affected	True

```
pidx =1 # participant index
p_data = df[df.participant == pidx]
alt.Chart(p_data).mark_bar().encode(
    x='biomarker',
    y='measurement',
    color=alt.Color(
        'affected_or_not:N'
    ),
    tooltip=['biomarker', 'affected_or_not', 'measurement']
).interactive().properties(
    title=f'Distribution of biomarker measurements for participant #{idx} (k_j = {p_data.k_j
)
```

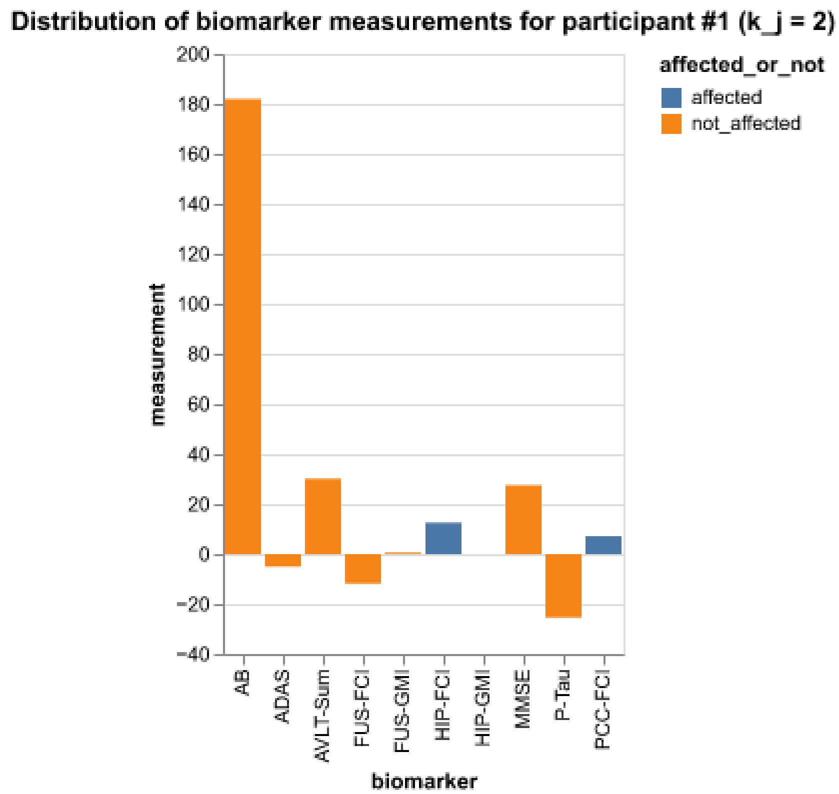

Figure 4.6: Distribution of biomarker measurements for a specific participant

5 Estimate Distribution Parameters

Given S, and a biomarker's measurements, how can we estimate $\mathcal{N}(\theta_\mu, \theta_\sigma)$ and $\mathcal{N}(\phi_\mu, \phi_\sigma)$?

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import altair as alt
import math
from scipy.stats import norm
from copkmeans.cop_kmeans import cop_kmeans
from typing import Dict
import re
import json
from collections import defaultdict
```

```
output_dir = 'data'
df = pd.read_csv(f"{output_dir}/150|200_3.csv")
biomarkers = df.biomarker.unique()
idx = 1
biomarker_df = df[df.biomarker==biomarkers[idx]]
biomarker_df.sample(10)
```

	participant	biomarker	measurement	k_j	S_n	affected_or_not	diseased
221	21	PCC-FCI	6.720331	0	2	not_affected	False
208	8	PCC-FCI	10.352851	0	2	not_affected	False
398	198	PCC-FCI	10.198974	0	2	not_affected	False
360	160	PCC-FCI	14.765535	0	2	not_affected	False
318	118	PCC-FCI	13.565672	0	2	not_affected	False
266	66	PCC-FCI	0.444082	8	2	affected	True
329	129	PCC-FCI	14.137447	0	2	not_affected	False
234	34	PCC-FCI	18.188517	0	2	not_affected	False
380	180	PCC-FCI	10.445202	0	2	not_affected	False
244	44	PCC-FCI	6.805627	8	2	affected	True

```
biomarker_df.shape
```

```
(200, 7)
```

5.1 Constrained K-Means

Tip

To use this algorithm, we only need to know (1) whether this participant is diseased; and (2) each biomarker measurement.

The first method we can use is constrained K-means, implemented by Babaki (2017).

We choose constrained K-Means instead of the standard K-Means algorithm because we know all healthy participants have to belong to the same cluster. The constrained K-Means algorithm can satisfy this constraint.

```
def compute_theta_phi_for_biomarker(biomarker_df):
    """get theta and phi parameters for this biomarker using constrained k-means
    input:
        - biomarker_df: a pd.dataframe of a specific biomarker
    output:
        - a tuple: theta_mean, theta_std, phi_mean, phi_std
    """
    n_clusters = 2
    measurements = np.array(biomarker_df['measurement']).reshape(-1, 1)
    healthy_df = biomarker_df[biomarker_df['diseased'] == False]
    must_link = [(x, 0) for x in healthy_df.index]
    # imeplement Constrained K-means algorithm
    # https://github.com/Behrouz-Babaki/COP-Kmeans
    clusters, centers = cop_kmeans(dataset=measurements, k=n_clusters, ml=must_link)
    predictions = np.array(clusters)
    healthy_predictions = predictions[healthy_df.index]

    # double check the result
    cluster_counts = np.bincount(predictions)
    if not all(c > 1 for c in cluster_counts):
        raise ValueError(f"Not all clusters have more than one node.")
    if len(cluster_counts) != n_clusters:
        raise ValueError(f"Number of clusters is not equal to {n_clusters}.")
```

```
    if len(set(healthy_predictions)) > 1:
        raise ValueError("Not all healthy participants belong to one cluster.")

    phi_cluster_idx = healthy_predictions[0]
    theta_cluster_idx = 1 - phi_cluster_idx

    # two empty clusters to strore measurements
    clustered_measurements = [[] for _ in range(2)]
    # Store measurements into their cluster
    for i, prediction in enumerate(predictions):
        clustered_measurements[prediction].append(measurements[i][0])

     # Calculate means and standard deviations
    theta_mean, theta_std = np.mean(
        clustered_measurements[theta_cluster_idx]), np.std(
            clustered_measurements[theta_cluster_idx])
    phi_mean, phi_std = np.mean(
        clustered_measurements[phi_cluster_idx]), np.std(
            clustered_measurements[phi_cluster_idx])

    # check whether the prior_theta_phi contain 0s or nan
    if math.isnan(theta_std) or theta_std == 0:
        raise ValueError(f"Invalid theta_std: {theta_std}")
    if math.isnan(phi_std) or phi_std == 0:
        raise ValueError(f"Invalid phi_std: {phi_std}")
    if theta_mean == 0 or math.isnan(theta_mean):
        raise ValueError(f"Invalid theta_mean: {theta_mean}")
    if phi_mean == 0 or math.isnan(phi_mean):
        raise ValueError(f"Invalid phi_mean: {phi_mean}")

    return theta_mean, theta_std, phi_mean, phi_std

def get_theta_phi_estimates(
    data: pd.DataFrame,
) -> Dict[str, Dict[str, float]]:
    """
    Obtain theta and phi estimates (mean and standard deviation) for each biomarker.

    Args:
    data (pd.DataFrame): DataFrame containing participant data with columns 'participant',
        'biomarker', 'measurement', and 'diseased'.
    # biomarkers (List[str]): A list of biomarker names.
```

```
    Returns:
    Dict[str, Dict[str, float]]: A dictionary where each key is a biomarker name,
        and each value is another dictionary containing the means and standard deviations
        for theta and phi of that biomarker, with keys 'theta_mean', 'theta_std', 'phi_mean'
        and 'phi_std'.
    """
    # empty hashmap of dictionaries to store the estimates
    estimates = {}
    biomarkers = data.biomarker.unique()
    for biomarker in biomarkers:
        # Filter data for the current biomarker
        # reset_index is necessary here because we will use healthy_df.index later
        biomarker_df = data[data['biomarker']
                            == biomarker].reset_index(drop=True)
        theta_mean, theta_std, phi_mean, phi_std = compute_theta_phi_for_biomarker(
            biomarker_df)
        estimates[biomarker] = {
            'theta_mean': theta_mean,
            'theta_std': theta_std,
            'phi_mean': phi_mean,
            'phi_std': phi_std
        }
    return estimates
```

```
cop_kmeans_estimates = get_theta_phi_estimates(data = df)
cop_kmeans_estimates_df = pd.DataFrame.from_dict(
    cop_kmeans_estimates, orient='index')
cop_kmeans_estimates_df.reset_index(names = 'biomarker', inplace=True)
cop_kmeans_estimates_df
```

	biomarker	theta_mean	theta_std	phi_mean	phi_std
0	HIP-FCI	-8.587833	5.365053	4.903437	2.008974
1	PCC-FCI	16.330398	0.720160	10.507041	4.427907
2	AB	152.194375	15.344414	252.969562	50.946400
3	P-Tau	-71.767059	15.231429	-23.737466	16.637657
4	MMSE	22.272803	1.624078	28.011392	0.805532
5	ADAS	-20.582091	3.853234	-6.002048	1.487443
6	HIP-GMI	0.793961	0.132461	0.365322	0.226494
7	AVLT-Sum	23.638988	5.848744	42.028039	14.229989
8	FUS-GMI	0.645942	0.019813	0.579887	0.067980

	biomarker	theta_mean	theta_std	phi_mean	phi_std
9	FUS-FCI	-19.200644	4.688806	-9.568412	3.003514

```
with open('files/real_theta_phi.json', 'r') as f:
    truth = json.load(f)
truth_df = pd.DataFrame.from_dict(truth, orient='index')
truth_df.reset_index(names = 'biomarker', inplace=True)
truth_df
```

	biomarker	theta_mean	theta_std	phi_mean	phi_std
0	MMSE	22.0	2.666667	28.0	0.666667
1	ADAS	-20.0	4.000000	-6.0	1.333333
2	AB	150.0	16.666667	250.0	50.000000
3	P-Tau	-50.0	33.333333	-25.0	16.666667
4	HIP-FCI	-5.0	6.666667	5.0	1.666667
5	HIP-GMI	0.3	0.333333	0.4	0.233333
6	AVLT-Sum	20.0	6.666667	40.0	15.000000
7	PCC-FCI	5.0	3.333333	12.0	4.000000
8	FUS-GMI	0.5	0.066667	0.6	0.066667
9	FUS-FCI	-20.0	6.000000	-10.0	3.333333

Now let's compare the results using plots:

```
def obtain_theta_phi_params(biomarker, estimate_df, truth):
    '''This is to obtain both true and estimated theta and phi params for each biomarker '''
    biomarker_data_est = estimate_df[estimate_df.biomarker == biomarker].reset_index()
    biomarker_data = truth[truth.biomarker == biomarker].reset_index()
    # theta for affected
    theta_mean_est = biomarker_data_est.theta_mean[0]
    theta_std_est = biomarker_data_est.theta_std[0]

    theta_mean = biomarker_data.theta_mean[0]
    theta_std = biomarker_data.theta_std[0]

    # phi for not affected
    phi_mean_est = biomarker_data_est.phi_mean[0]
    phi_std_est = biomarker_data_est.phi_std[0]

    phi_mean = biomarker_data.phi_mean[0]
```

```
    phi_std = biomarker_data.phi_std[0]

    return theta_mean, theta_std, theta_mean_est, theta_std_est, phi_mean, phi_std, phi_mean_

def make_chart(biomarkers, estimate_df, truth, title):
    alt.renderers.enable('png')
    charts = []
    for biomarker in biomarkers:
        theta_mean, theta_std, theta_mean_est, theta_std_est, phi_mean, phi_std, phi_mean_es
        biomarker, estimate_df, truth)
        mean1, std1 = theta_mean, theta_std
        mean2, std2 = theta_mean_est, theta_std_est

        # Generating points on the x axis
        x_thetas = np.linspace(min(mean1 - 3*std1, mean2 - 3*std2),
                        max(mean1 + 3*std1, mean2 + 3*std2), 1000)

        # Creating DataFrames for each distribution
        df1 = pd.DataFrame({'x': x_thetas, 'pdf': norm.pdf(x_thetas, mean1, std1), 'Distribu
        df2 = pd.DataFrame({'x': x_thetas, 'pdf': norm.pdf(x_thetas, mean2, std2), 'Distribu

        # Combining the DataFrames
        df3 = pd.concat([df1, df2])

        # Altair plot
        chart_theta = alt.Chart(df3).mark_line().encode(
            x='x',
            y='pdf',
            color=alt.Color('Distribution:N', legend=alt.Legend(title="Theta"))
        ).properties(
            title=f'{biomarker}, Theta',
            width=100,
            height=100
            )

        mean1, std1 = phi_mean, phi_std
        mean2, std2 = phi_mean_est, phi_std_est

        # Generating points on the x axis
        x_phis = np.linspace(min(mean1 - 3*std1, mean2 - 3*std2),
                        max(mean1 + 3*std1, mean2 + 3*std2), 1000)
```

```
        # Creating DataFrames for each distribution
        df1 = pd.DataFrame({'x': x_phis, 'pdf': norm.pdf(x_phis, mean1, std1), 'Distribution
        df2 = pd.DataFrame({'x': x_phis, 'pdf': norm.pdf(x_phis, mean2, std2), 'Distribution

        # Combining the DataFrames
        df3 = pd.concat([df1, df2])

        # Altair plot
        chart_phi = alt.Chart(df3).mark_line().encode(
            x='x',
            y='pdf',
            color=alt.Color('Distribution:N', legend=alt.Legend(title="Phi"))
        ).properties(
            title=f'{biomarker}, Phi',
            width=100,
            height=100
            )

        # Concatenate theta and phi charts horizontally
        hconcat_chart = alt.hconcat(chart_theta, chart_phi).resolve_scale(color="independent"

        # Append the concatenated chart to the list of charts
        charts.append(hconcat_chart)
    # Concatenate all the charts vertically
    final_chart = alt.vconcat(*charts).properties(title = title)

    # Display the final chart
    final_chart.display()
```

```
make_chart(
    biomarkers[0:4],
    cop_kmeans_estimates_df,
    truth_df,
    title = "Comparing Theta and Phi Distributions Using Constrained K-Means"
)
```

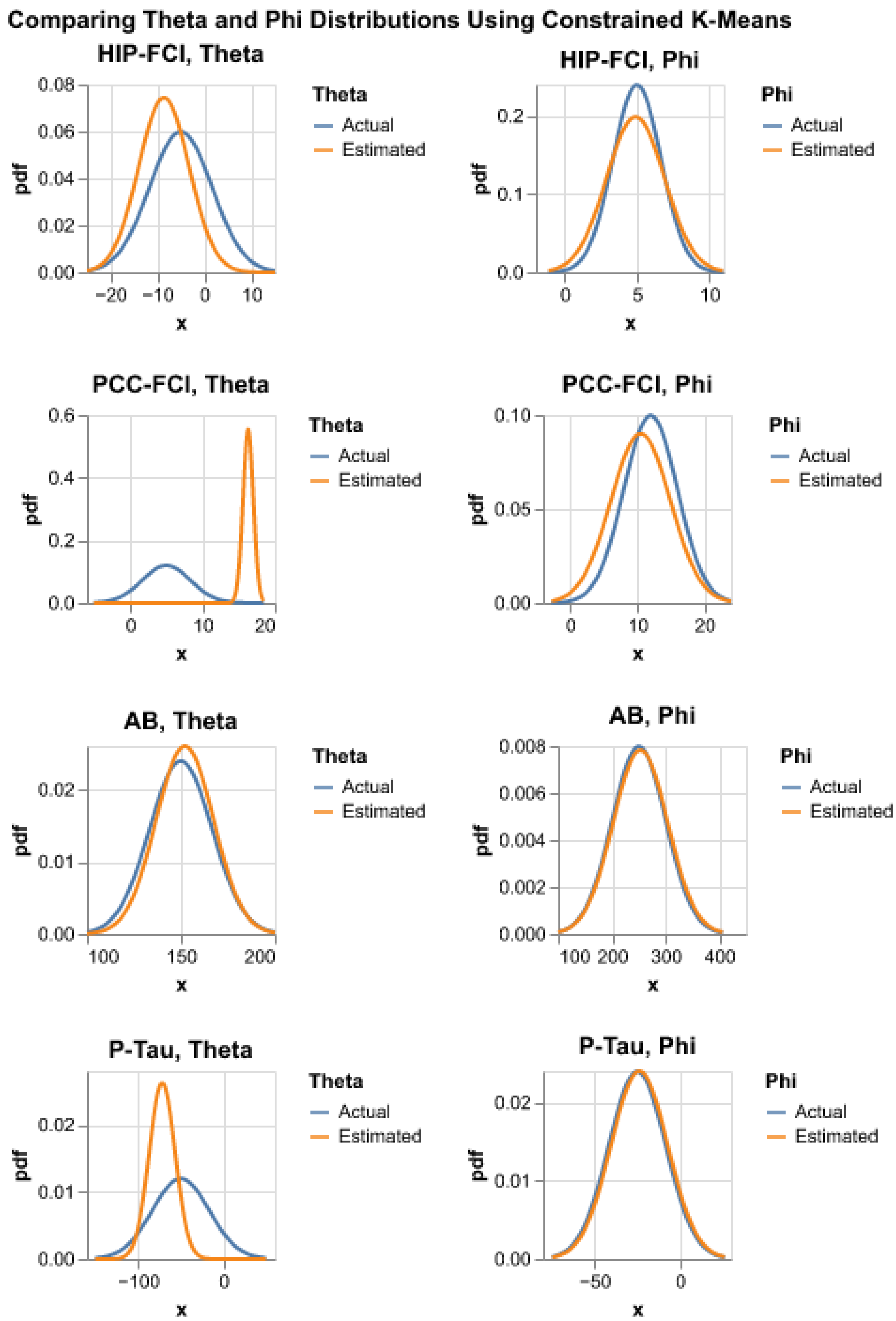

Figure 5.1: Comparing Theta and Phi Distributions Using Constrained K-Means

It turns out the result is not very desriable.

5.2 Conjugate Priors

The second method we may utilize is conjugate priors. Conjugacy occurs when the posterior distribution is in the same family of distribution as the prior distribution, but with new parameter values.

Why conjugacy is important? Because without it, one has to do the integration, which oftentimes is hard.

Three major conjugate families:

- Beta-Binomial
- Gamma-Poisson
- Normal-Normal

In our example, we assume that the measurement data for each biomarker follows a normal distribution; however, we do not know the exact μ and σ. Our job is to estimate the two parameters for each biomarker based on the data we have.

According to *An Introduction to Bayesian Thinking* by Clyde et al. (2022), if the data comes from a normal distribution with unknown μ and σ, the conjugate prior for μ has a normal distribution with mean m_0 and variance $\frac{\sigma^2}{n_0}$. The conjugate prior for $\frac{1}{\sigma^2}$ has a Gamma distribution with shape $\frac{v_0}{2}$ and rate $\frac{v_0 s_0^2}{2}$ where

- m_0: prior estimate of μ.
- n_0: how strongly is the prior belief in m_0 is held.
- s_0^2: prior estimate of σ^2.
- v_0: prior degress of freedome, influencing the certainty of s_0^2.

That is to say:

$$\mu|\sigma^2 \sim \mathcal{N}(m_0, \sigma^2/n_0)$$

$$1/\sigma^2 \sim Gamma\left(\frac{v_0}{2}, \frac{v_0 s_0^2}{2}\right)$$

Combined, we have:

$$(\mu, 1/\sigma^2) \sim NormalGamma(m_0, n_0, s_0^2, v_0)$$

The posterior also follows a Normal-Gamma distribution:

$$(\mu, 1/\sigma^2)|data \sim NormalGamma(m_n, n_n, s_n^2, v_n)$$

More specifically

$$1/\sigma^2|data \sim Gamma(v_n/2, s_n^2 v_n/2)$$

$$\mu|data, \sigma^2 \sim \mathcal{N}(m_n, \sigma^2/n_n)$$

Based on the above two equations, we know that the mean of posterior mean is m_n and the mean of the posterior variance is $(s_n^2 v_n/2)/(v_n/2)$. This is beceause the expected value of $Gamma(\alpha, \beta)$ is $\frac{\alpha}{\beta}$.

where

- m_n: posterior mean, mode, and median for μ
- n_n: posterior sample size
- s_n^2: posterior variance
- v_n: posterior degrees of freedome

The updating rules to get the new hyper-parameters:

$$m_n = \frac{n}{n+n_0}\bar{y} + \frac{n_0}{n+n_0}m_0$$

$$n_n = n_0 + n$$

$$v_n = v_0 + n$$

$$s_n^2 = \frac{1}{v_n}\left[s^2(n-1) + s_0^2 v_0 + \frac{n_0 n}{n_n}(\bar{y} - m_0)^2\right]$$

where

- n: sample size
- $\bar{y}$: sample mean
- s^2: sample variance

Tip

To apply the algorithm of conjugate priors, we assume we already know S and k_j, alongside biomarker measurement (X_{nj}). Based on S and k_j, we can infer whether a biomarker is affected by the disease or not.

```
def estimate_params_exact(m0, n0, s0_sq, v0, data):
    '''This is to estimate means and vars based on conjugate priors
    Inputs:
        - data: a vector of measurements
        - m0: prior estimate of $\mu$.
        - n0: how strongly is the prior belief in $m_0$ is held.
        - s0_sq: prior estimate of $\sigma^2$.
        - v0: prior degress of freedome, influencing the certainty of $s_0^2$.

    Outputs:
        - mu estiate, std estimate
    '''
    # Data summary
    sample_mean = np.mean(data)
    sample_size = len(data)
    sample_var = np.var(data, ddof=1)  # ddof=1 for unbiased estimator

    # Update hyperparameters for the Normal-Inverse Gamma posterior
    updated_m0 = (n0 * m0 + sample_size * sample_mean) / (n0 + sample_size)
    updated_n0 = n0 + sample_size
    updated_v0 = v0 + sample_size
    updated_s0_sq = (1 / updated_v0) * ((sample_size - 1) * sample_var + v0 * s0_sq +
                                    (n0 * sample_size / updated_n0) * (sample_mean - m0)
    updated_alpha = updated_v0/2
    updated_beta = updated_v0*updated_s0_sq/2

    # Posterior estimates
    mu_posterior_mean = updated_m0
    sigma_squared_posterior_mean = updated_beta/updated_alpha

    mu_estimation = mu_posterior_mean
    std_estimation = np.sqrt(sigma_squared_posterior_mean)

    return mu_estimation, std_estimation

def get_theta_phi_conjugate_priors(biomarkers, data_we_have, theta_phi_kmeans):
```

```
'''To get estimated parameters, returns a hashmap
Input:
- biomarkers: biomarkers
- data_we_have: participants data filled with initial or updated participant_stages
- theta_phi_kmeans: a hashmap of dicts, which are the prior theta and phi values
    obtained from the initial constrained kmeans algorithm

Output:
- a hashmap of dictionaries. Key is biomarker name and value is a dictionary.
Each dictionary contains the theta and phi mean/std values for a specific biomarker.
'''
# empty list of dictionaries to store the estimates
hashmap_of_means_stds_estimate_dicts = {}

for biomarker in biomarkers:
    # Initialize dictionary outside the inner loop
    dic = {'biomarker': biomarker}
    for affected in ['affected', 'not_affected']:
        data_full = data_we_have[(data_we_have.biomarker == biomarker) & (
            data_we_have.affected_or_not == affected)]
        if len(data_full) > 1:
            measurements = data_full.measurement
            s0_sq = np.var(measurements, ddof=1)
            m0 = np.mean(measurements)
            mu_estimate, std_estimate = estimate_params_exact(
                m0=m0, n0=1, s0_sq=s0_sq, v0=1, data=measurements)
            if affected == 'affected':
                dic['theta_mean'] = mu_estimate
                dic['theta_std'] = std_estimate
            else:
                dic['phi_mean'] = mu_estimate
                dic['phi_std'] = std_estimate
        # If there is only one observation or not observation at all, resort to theta_phi
        # YES, IT IS POSSIBLE THAT DATA_FULL HERE IS NULL
        # For example, if a biomarker indicates stage of (num_biomarkers), but all partic
        # are smaller than that stage; so that for all participants, this biomarker is no
        else:
            print('not enough data here, so we have to use theta phi estimates from cons
            # print(theta_phi_kmeans)
            if affected == 'affected':
                dic['theta_mean'] = theta_phi_kmeans[biomarker]['theta_mean']
                dic['theta_std'] = theta_phi_kmeans[biomarker]['theta_std']
```

```python
                else:
                    dic['phi_mean'] = theta_phi_kmeans[biomarker]['phi_mean']
                    dic['phi_std'] = theta_phi_kmeans[biomarker]['phi_std']
        # print(f"biomarker {biomarker} done!")
        hashmap_of_means_stds_estimate_dicts[biomarker] = dic
    return hashmap_of_means_stds_estimate_dicts
```

```python
conjugate_prior_theta_phi = get_theta_phi_conjugate_priors(
    biomarkers = biomarkers,
    data_we_have = df,
    theta_phi_kmeans = cop_kmeans_estimates
)
cp_df = pd.DataFrame.from_dict(conjugate_prior_theta_phi, orient='index')
cp_df.reset_index(drop=True, inplace=True)
cp_df
```

	biomarker	theta_mean	theta_std	phi_mean	phi_std
0	HIP-FCI	-5.378366	7.233991	5.092800	1.514402
1	PCC-FCI	5.521792	2.777207	12.071769	3.671679
2	AB	151.143708	14.806694	251.973564	51.382188
3	P-Tau	-41.768257	34.857945	-24.739527	14.928907
4	MMSE	23.122406	2.446874	28.049683	0.718493
5	ADAS	-19.633304	4.582900	-5.902198	1.278311
6	HIP-GMI	0.425625	0.272876	0.379542	0.235348
7	AVLT-Sum	21.664360	3.755735	40.700638	14.480463
8	FUS-GMI	0.482745	0.055585	0.590434	0.063730
9	FUS-FCI	-18.566905	5.781937	-9.648705	3.099195

Note

When we estimate θ and ϕ using conjugate priors, we need to use the result from constrained kmeans as a fall back because it is possible that for a specific biomarker, either the `affected` or the `not_affected` group is empty. If that is the case, we are not able to estimate relevant parameters and have to resort to the fallback result.

```python
make_chart(
    biomarkers[0:4],
    cp_df,
    truth_df,
```

```
    title = "Comparing Theta and Phi Distributions Using Conjugate Priors"
)
```

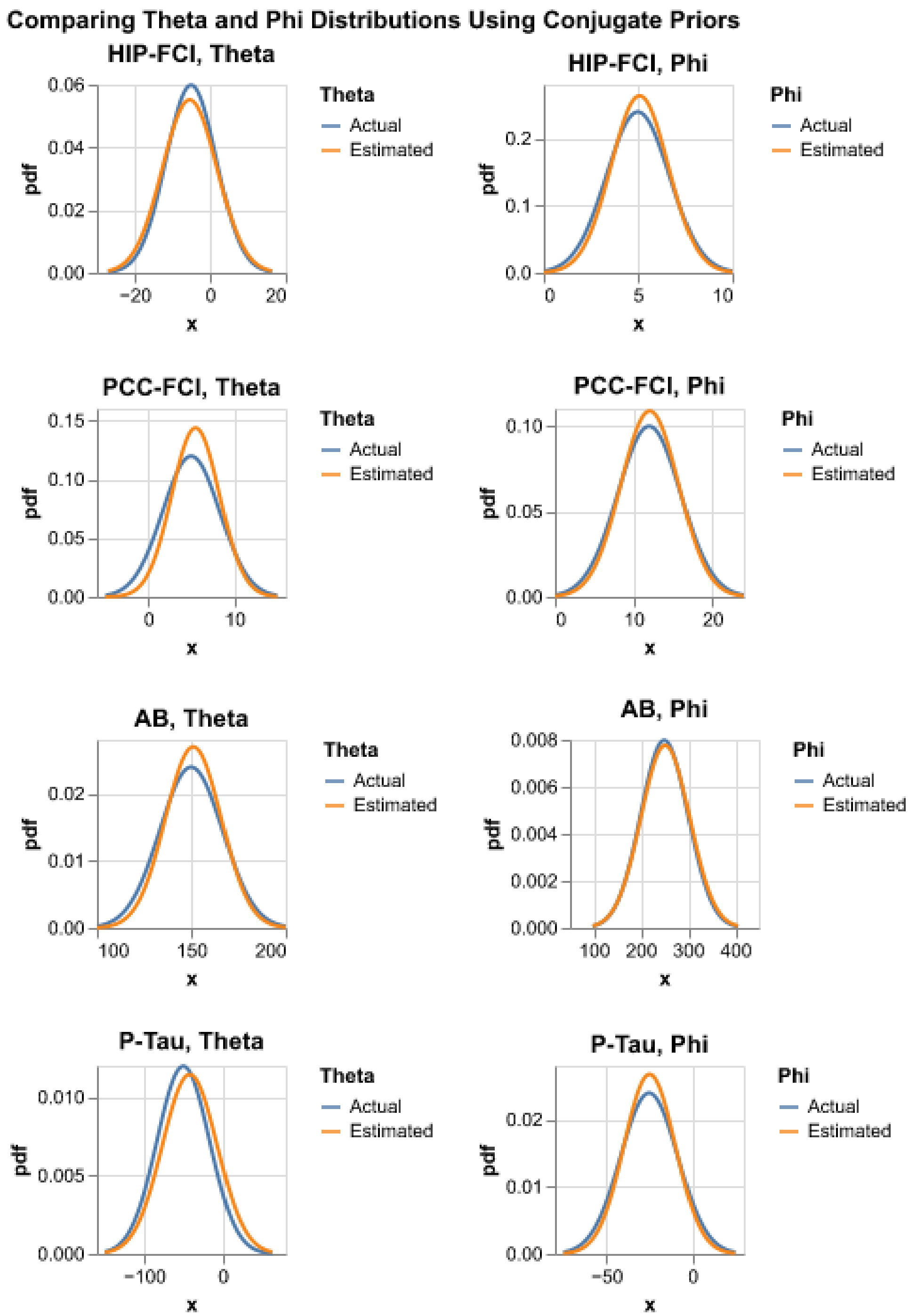

Figure 5.2: Comparing Theta and Phi Distributions Using Conjugate Prior

5.3 Soft K-Means

Conjugate Priors assumes we know k_j, which often times is not already known. Constrained K-Means is only taking advantage of X_{nj} and whether participants are diseased or not, leaving S, which is known to us, unexploited.

Soft K-Means is a good alternative to these two because it utilizes S while at the same time not assuming we know k_j.

The logic of soft-kmeans is this;

1. If a participant is diseased, we iterate through all possible disease stages, and calculate the associated likelihood using Equation 3.1. We then normalize these likelihoods to obtain the estimated probability of this participant being at each stage. For example, if there are three possible stages, and the associated likelihoods are `[1, 3, 6]`, then the normalized likelihoods would be `[0.1, 0.3, 0.6]`.

> **Tip**
>
> You may wonder how we can use Equation 3.1 when we do not know θ and ϕ yet (which is exactly what we are trying to do!). If you notice this, it is a very keen observation!. If fact, we are going to use the estimated θ and ϕ we obtained above using constrained K-Means.

2. For each biomarker n, we obtain S_n based on S. Then we iterate through all participants. If this participant is healthy, we include their biomarker measurement in `cluster_phi`. If this participant is diseased, we compare between P_θ and P_ϕ. If $S_n = 2$, then $P_\theta = 0.1{+}0.3 = 0.4$ and $P_\phi = 0.6$. Because P_ϕ is larger, we include this participant's biomarker measurement in `cluster_phi`. When the iteration through participants is done, we can calculate the mean and standard deviation of each cluster.

> **Tip**
>
> If $P_\theta = P_\phi$, we randomly assign this participant's biomarker measurement to a cluster.

```python
def compute_single_measurement_likelihood(theta_phi, biomarker, affected, measurement):
    '''Computes the likelihood of the measurement value of a single biomarker

    We know the normal distribution defined by either theta or phi
    and we know the measurement. This will give us the probability
    of this given measurement value.

    input:
```

```
    - theta_phi: the dictionary containing theta and phi values for each biomarker
    - biomarker: an integer between 0 and 9
    - affected: boolean
    - measurement: the observed value for a biomarker in a specific participant

    output: a scalar
    '''
    biomarker_dict = theta_phi[biomarker]
    mu = biomarker_dict['theta_mean'] if affected else biomarker_dict['phi_mean']
    std = biomarker_dict['theta_std'] if affected else biomarker_dict['phi_std']
    var = std**2
    if var <= int(0) or np.isnan(measurement) or np.isnan(mu):
        print(f"Invalid values: measurement: {measurement}, mu: {mu}, var: {var}")
        likelihood = np.exp(-(measurement - mu)**2 /
                            (2 * var)) / np.sqrt(2 * np.pi * var)
    else:
        likelihood = np.exp(-(measurement - mu)**2 /
                            (2 * var)) / np.sqrt(2 * np.pi * var)
    return likelihood

def fill_up_kj_and_affected(pdata, k_j):
    '''Fill up a single participant's data using k_j; basically add two columns:
    k_j and affected
    Note that this function assumes that pdata already has the S_n column

    Input:
    - pdata: a dataframe of ten biomarker values for a specific participant
    - k_j: a scalar
    '''
    data = pdata.copy()
    data['k_j'] = k_j
    data['affected'] = data.apply(lambda row: row.k_j >= row.S_n, axis=1)
    return data

def compute_likelihood(pdata, k_j, theta_phi):
    '''
    This function computes the likelihood of seeing this sequence of biomarker values
    for a specific participant, assuming that this participant is at stage k_j
    '''
    data = fill_up_kj_and_affected(pdata, k_j)
    likelihood = 1
    for i, row in data.iterrows():
```

```
        biomarker = row['biomarker']
        measurement = row['measurement']
        affected = row['affected']
        likelihood *= compute_single_measurement_likelihood(
            theta_phi, biomarker, affected, measurement)
    return likelihood

def obtain_participants_hashmap(
        data,
        prior_theta_phi_estimates,
):
    """
    Input:
        - data: a pd.dataframe. For exrample, 150|200_3.csv
        - prior_theta_phi_estimates, a hashmap of dicts.
            This is the result from constrained kmeans

    Output:
        - hashmap: a dictionary whose key is participant id
            and value value is a dict whose key is stage
            and value is normalized likelihood
    """
    # initialize hashmap_of_normalized_stage_likelihood_dicts
    participants_hashmap = {}
    non_diseased_participants = data[
        data.diseased == False]['participant'].unique()
    disease_stages = data.S_n.unique()
    for p in data.participant.unique():
        dic = defaultdict(int)
        pdata = data[data.participant == p].reset_index(drop = True)
        if p in non_diseased_participants:
            dic[0] = 1
        else:
            for k_j in disease_stages:
                kj_ll = compute_likelihood(pdata, k_j, prior_theta_phi_estimates)
                dic[k_j] = kj_ll
            # likelihood sum
            sum_ll = sum(dic.values())
            epsilon = 1e-10
            if sum_ll == 0:
                sum_ll = epsilon
            normalized_lls = [l/sum_ll for l in dic.values()]
```

```
            normalized_ll_dict = dict(zip(disease_stages, normalized_lls))
            participants_hashmap[p] = normalized_ll_dict
    return participants_hashmap

def calc_soft_kmeans_for_biomarker(
        data,
        biomarker,
        participants_hashmap

):
    """obtain theta, phi estimates using soft kmeans for a single biomarker
    Inputs:
        - data: a pd.dataframe. For example, 150|200_3.csv
        - biomarker: a str, a certain biomarker name
        - hashmap: a dict, returned result of obtain_hashmap()
    Outputs:
        - theta_mean, theta_std, phi_mean, phi_std, a tuple of floats
    """
    non_diseased_participants = data[
        data.diseased == False]['participant'].unique()
    disease_stages = data.S_n.unique()
     # DataFrame for this biomarker
    biomarker_df = data[
        data['biomarker'] == biomarker].reset_index(
            drop=True).sort_values(
                by = 'participant', ascending = True)
    # Extract measurements
    measurements = np.array(biomarker_df['measurement'])

    this_biomarker_order = biomarker_df.S_n[0]

    affected_cluster = []
    non_affected_cluster = []

    for p in data.participant.unique():
        if p in non_diseased_participants:
            non_affected_cluster.append(measurements[p])
        else:
            normalized_ll_dict = participants_hashmap[p]
            affected_prob = sum(
                normalized_ll_dict[
                    kj] for kj in disease_stages if kj >= this_biomarker_order)
```

```
            non_affected_prob = sum(
                normalized_ll_dict[
                    kj] for kj in disease_stages if kj < this_biomarker_order)
            if affected_prob > non_affected_prob:
                    affected_cluster.append(measurements[p])
            elif affected_prob < non_affected_prob:
                non_affected_cluster.append(measurements[p])
            else:
                # Assign to either cluster randomly if probabilities are equal
                if np.random.random() > 0.5:
                    affected_cluster.append(measurements[p])
                else:
                    non_affected_cluster.append(measurements[p])
    # Compute means and standard deviations
    theta_mean = np.mean(affected_cluster) if affected_cluster else np.nan
    theta_std = np.std(affected_cluster) if affected_cluster else np.nan
    phi_mean = np.mean(
        non_affected_cluster) if non_affected_cluster else np.nan
    phi_std = np.std(non_affected_cluster) if non_affected_cluster else np.nan
    return theta_mean, theta_std, phi_mean, phi_std

def cal_soft_kmeans_for_biomarkers(
        data,
        participants_hashmap,
        prior_theta_phi_estimates,
):
    soft_kmeans_estimates = {}
    biomarkers = data.biomarker.unique()
    for biomarker in biomarkers:
        dic = {'biomarker': biomarker}
        prior = prior_theta_phi_estimates[biomarker]
        theta_mean, theta_std, phi_mean, phi_std = calc_soft_kmeans_for_biomarker(
            data, biomarker, participants_hashmap
        )
        if theta_std == 0 or math.isnan(theta_std):
            theta_mean = prior['theta_mean']
            theta_std = prior['theta_std']
        if phi_std == 0 or math.isnan(phi_std):
            phi_mean = prior['phi_mean']
            phi_std = prior['phi_std']
        dic['theta_mean'] = theta_mean
        dic['theta_std'] = theta_std
```

```
        dic['phi_mean'] = phi_mean
        dic['phi_std'] = phi_std
        soft_kmeans_estimates[biomarker] = dic
    return soft_kmeans_estimates
```

```
participants_hashmap = obtain_participants_hashmap(
    data = df,
    prior_theta_phi_estimates = cop_kmeans_estimates,
)

soft_kmeans_estimates = cal_soft_kmeans_for_biomarkers(
        data = df,
        participants_hashmap = participants_hashmap,
        prior_theta_phi_estimates = cop_kmeans_estimates,
)
```

```
soft_kmeans_estimates_df = pd.DataFrame.from_dict(
    soft_kmeans_estimates, orient='index')
soft_kmeans_estimates_df.reset_index(drop=True, inplace=True)
soft_kmeans_estimates_df
```

	biomarker	theta_mean	theta_std	phi_mean	phi_std
0	HIP-FCI	-5.378366	7.232544	5.092800	1.514369
1	PCC-FCI	10.397606	3.698129	10.572261	4.472485
2	AB	157.514640	19.654237	232.546088	61.426283
3	P-Tau	-61.280491	21.704315	-27.032696	20.645375
4	MMSE	21.478486	0.869996	27.414771	1.956947
5	ADAS	-23.386222	3.249392	-7.343264	4.453207
6	HIP-GMI	0.636480	0.017335	0.382067	0.240018
7	AVLT-Sum	23.638988	5.848744	39.259784	14.847938
8	FUS-GMI	0.645942	0.019813	0.584511	0.067892
9	FUS-FCI	-19.200644	4.688806	-10.050024	3.751844

```
make_chart(
    biomarkers[0:4],
    soft_kmeans_estimates_df,
    truth_df,
    title = "Comparing Theta and Phi Distributions Using Soft K-Means"
)
```

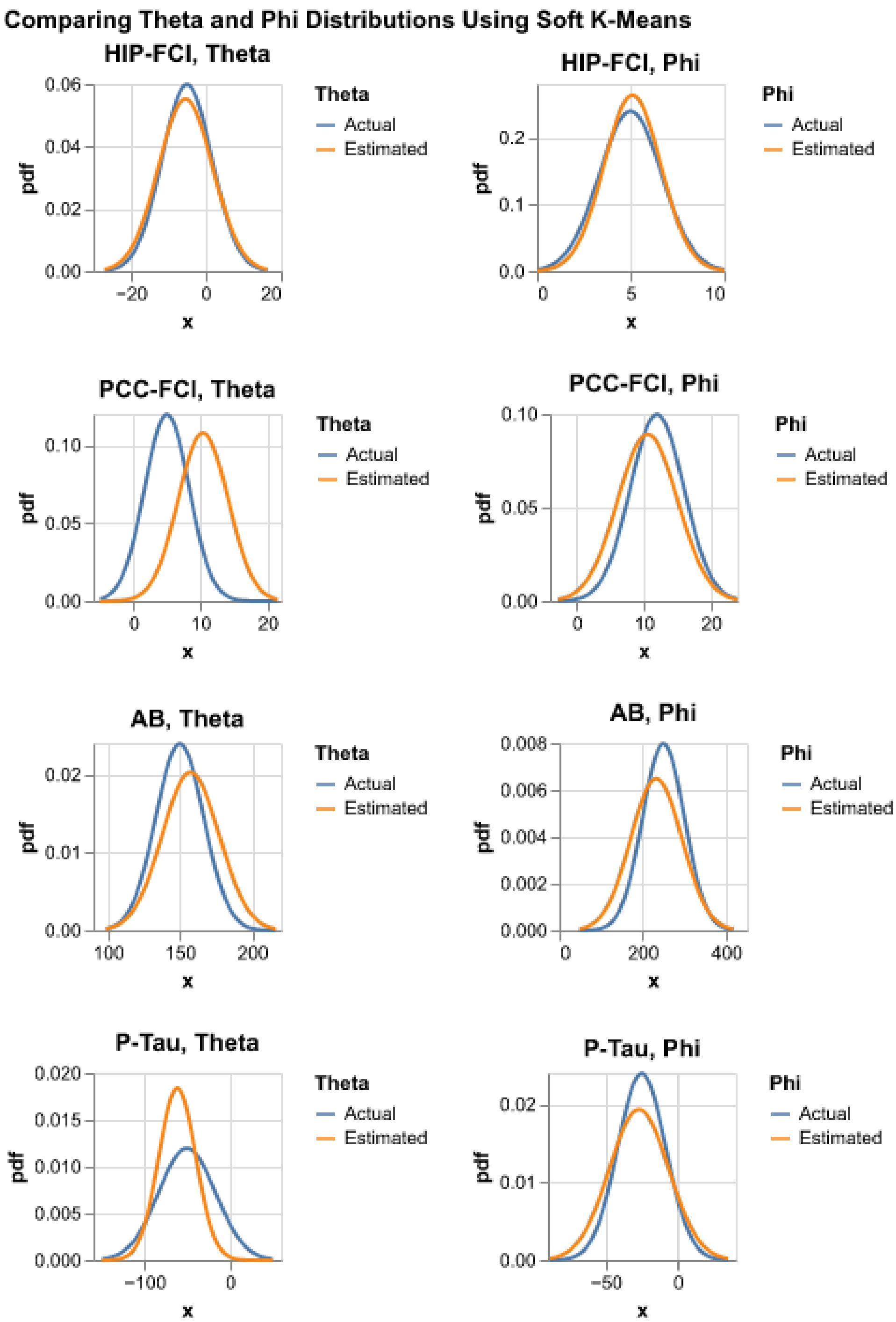

Figure 5.3: Comparing Theta and Phi Distributions Using Soft K-Mean

5.4 Conclusion

We compare the above three methods. Constrained k-means has the least number of prerequisites: it only needs to know whether participants are healthy or not and biomarker measurements. However, the drawback is that it might be very accurate. Conjugate priors are extremely accurate; however, it requires that we know almost everything: besides what is required by constrained k-kmeans, it also needs to know S and k_j. Soft k-kmeans does not require the knowledge of k_j and is an improvement over constrained k-means.

We also noticed that both conjugate priors and soft k-means need the result from constrained k-means as a fallback.

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