Gradient Descent Optimization

Function to maximize:

$$\hat{h} = \arg\max_{h \in \mathcal{H}} P(S|h)P(h) \tag{1}$$

Then: Naive Bayes:

$$\hat{h} = \arg\max_{h \in \mathcal{H}} P(h) \prod_{d=1}^{D} P(s_d|h) \tag{2}$$

Then: since h is composed by K-zones:

$$\hat{h} = \arg\max_{h \in \mathcal{H}} \prod_{k=1}^{K} \prod_{d=1}^{|S_t|} P(s_d|h_k)P(h_k) \tag{3}$$

where S_k is the sub-set of sites that belongs into the layout zone k.
From here we work under the constrain of a single main zone defined by its corners $(\boldsymbol{u}, \boldsymbol{b})$
Then: $P(h_k)$ is divided in its components:

$$\hat{h} = \arg\max_{h \in \mathcal{H}} \prod_{k=1}^{K} \prod_{d=1}^{|S_k|} P(s_d|(\boldsymbol{u}_k, \boldsymbol{b}_k))P(\boldsymbol{u}_k, \boldsymbol{b}_k) \tag{4}$$

Then: applying log:

$$\begin{aligned} \log \hat{h} &= \arg\max_{h \in \mathcal{H}} \log \prod_{k=1}^{K} \prod_{d=1}^{|S_k|} P(s_d|(\boldsymbol{u}_k, \boldsymbol{b}_k))P(\boldsymbol{u}_k, \boldsymbol{b}_k) \\ &= \arg\max_{h \in \mathcal{H}} \sum_{k=1}^{K} \sum_{d=1}^{|S_k|} \log P(s_d|(\boldsymbol{u}_k, \boldsymbol{b}_k)) + \log P(\boldsymbol{u}_k, \boldsymbol{b}_k) \end{aligned} \tag{5}$$

Now we want to search for the best $(\boldsymbol{u}_k^{i+1}, \boldsymbol{b}_k^{i+1})$ after some $(\boldsymbol{u}_k^{i}, \boldsymbol{b}_k^{i})$, in order to do that we can use gradient descent optimization over Eq. 5.

First for $\boldsymbol{u}_k$:

$$\begin{aligned}
\boldsymbol{u}_k^{i+1} &= \boldsymbol{u}_k^i - \alpha \frac{\delta h}{\delta \boldsymbol{u}_k^i} \\
&= \boldsymbol{u}_k^i - \alpha \frac{\delta}{\delta \boldsymbol{u}_k^i} \sum_{k=1}^{K} \sum_{d=1}^{|S_k|} \log P(s_d | (\boldsymbol{u}_k, \boldsymbol{b}_k)) + \log P(\boldsymbol{u}_k, \boldsymbol{b}_k) \\
&= \boldsymbol{u}_k^i - \alpha \sum_{k=1}^{K} \sum_{d=1}^{|S_k|} \left(\overbrace{\frac{\delta}{\delta \boldsymbol{u}_k^i} \log P(s_d | (\boldsymbol{u}_k, \boldsymbol{b}_k))}^{\gamma} + \underbrace{\frac{\delta}{\delta \boldsymbol{u}_k^i} \log P(\boldsymbol{u}_k, \boldsymbol{b}_k)}_{\beta} \right)
\end{aligned} \tag{6}$$

Now, we can take γ and β separately:
For β:

$$\begin{aligned}
\beta &= \frac{\delta}{\delta \boldsymbol{u}_k^i} \log P(\boldsymbol{u}_k^i) P(\boldsymbol{b}_k^i) \\
&= \frac{\delta}{\delta \boldsymbol{u}_k^i} \log \sum_{g=1}^{G_{\boldsymbol{u}_k^i}} \phi_g \mathcal{N}(\boldsymbol{u}_k^i, \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g) + \cancelto{0}{\frac{\delta}{\delta \boldsymbol{u}_k^i} \log \sum_{g=1}^{G_{\boldsymbol{b}_k^i}} \phi_g \mathcal{N}(\boldsymbol{b}_k^i, \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g)}
\end{aligned}$$

Using: $\frac{\delta \log f(x)}{\delta x} = \frac{1}{f(x)} \frac{\delta f(x)}{\delta x}$

$$= \underbrace{\frac{1}{\sum_{g=1}^{G_{\boldsymbol{u}_k^i}} \phi_g \mathcal{N}(\boldsymbol{u}_k^i, \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g)}}_{D} \frac{\delta}{\delta \boldsymbol{u}_k^i} \sum_{g=1}^{G_{\boldsymbol{u}_k^i}} \phi_g \mathcal{N}(\boldsymbol{u}_k^i, \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g)$$

Using: (where GMM is defined)

$$= D \sum_{g=1}^{G_{\boldsymbol{u}_k^i}} \phi_g (2\pi)^{G_{\boldsymbol{u}_k^i}/2} |\boldsymbol{\Sigma}_g|^{-1/2} \frac{\delta}{\delta \boldsymbol{u}_k^i} \exp^{-1/2(\boldsymbol{u}_k^i - \boldsymbol{\mu}_g)^T \boldsymbol{\Sigma}_g^{-1} (\boldsymbol{u}_k^i - \boldsymbol{\mu}_g)}$$

Using: $\frac{\delta \exp^{f(x)}}{\delta x} = \exp^{f(x)} \frac{\delta f(x)}{\delta x}$

$$= D \sum_{g=1}^{G_{\boldsymbol{u}_k^i}} \phi_g \underbrace{(2\pi)^{G_{\boldsymbol{u}_k^i}/2} |\boldsymbol{\Sigma}_g|^{-1/2} \exp^{-1/2(\boldsymbol{u}_k^i - \boldsymbol{\mu}_g)^T \boldsymbol{\Sigma}_g^{-1} (\boldsymbol{u}_k^i - \boldsymbol{\mu}_g)}}_{\mathcal{N}(\boldsymbol{u}_k^i, \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g)} \frac{\delta}{\delta \boldsymbol{u}_k^i} \left(-1/2 (\boldsymbol{u}_k^i - \boldsymbol{\mu}_g)^T \boldsymbol{\Sigma}_g^{-1} (\boldsymbol{u}_k^i - \boldsymbol{\mu}_g) \right)$$

Using: Lemma 6.2.3 for symmetric $\boldsymbol{\Sigma}_g^{-1}$ [1]

$$
\begin{aligned}
&= D \sum_{g=1}^{G_{\boldsymbol{u}_k^i}} \phi_g \mathcal{N}(\boldsymbol{u}_k^i, \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g)(\boldsymbol{u}_k^i - \boldsymbol{\mu}_g)^T \boldsymbol{\Sigma}_g^{-1} \\
&= \frac{\sum_{g=1}^{G_{\boldsymbol{u}_k^i}} \phi_g \mathcal{N}(\boldsymbol{u}_k^i, \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g)(\boldsymbol{u}_k^i - \boldsymbol{\mu}_g)^T \boldsymbol{\Sigma}_g^{-1}}{\sum_{g=1}^{G_{\boldsymbol{u}_k^i}} \phi_g \mathcal{N}(\boldsymbol{u}_k^i, \boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g)}
\end{aligned}
\tag{7}
$$

Now, for γ; due nature γ an analytic solution is very hard to obtain, so instead a geometric approach is followed.
Using one dimensional Five-Points Stencil [1] method on each axis we can obtain the first derivative on the point $(\boldsymbol{u}_k^i, \boldsymbol{b}_k^i)$:

$$\gamma = ?? \tag{8}$$

Is correct to use each dimension independently instead the Laplacian??

[1] $f'(x) \approx \frac{-f(x+2h)+8f(x+h)-8f(x-h)+f(x-2h)}{12h}$; h = space between points in the grid

References

[1] Luo, Y. Local Gradient Descent Methods for GMM Simplification. Tech. rep., 2015.