$$= \times^{\tau} \cdot \begin{bmatrix} A \cdot L \times \\ \vdots \\ A \cdot L \times \end{bmatrix}$$

$$= A_n \times_1^2 + A_{12} \times_1 \times_2 + \cdots + A_{1d} \times_1 \times_d$$

et
$$x^{T} = \begin{bmatrix} x^{T} & - \cdots & x^{T} & x^{T} \\ x^{T} & x^{T} & x^{T} & x^{T} \end{bmatrix}$$

= B. (symmetric)

$$= \sum_{i=1}^{d} A_{1i} x_{1} x_{1} + \sum_{j=1}^{d} A_{2j} x_{2} x_{2} + x_{j} + \cdots + \sum_{j=1}^{d} A_{dj} x_{d} x_{d}$$

$$P(D|\Sigma) = \prod_{n=1}^{N} \left\{ \frac{1}{(\lambda^n)^{d/2} |\Sigma|^2} \cdot e^{\chi} p \left\{ -\frac{1}{2} (\chi_n - \mu)^T \Sigma^T (\chi_n - \mu) \right\} \right\}$$

$$= \left(\frac{1}{(3\pi)^{d/2}} \sum_{|\mathcal{E}|^{\frac{1}{2}}}^{N} \cdot \exp\left\{\sum_{h=1}^{N} -\frac{1}{2} (x_h - y_h)^{T} \sum_{h=1}^{N} (x_h - y_h)^{T} \right\}$$

$$=\frac{1}{(2\pi)^{Nd/2}}\left[\mathbb{Z}^{\frac{1}{N/2}}\exp\left\{-\frac{1}{2}\operatorname{tr}\left[\sum_{n=1}^{N}\mathbb{S}^{\frac{1}{N}}(x_{n}-\mu)^{\frac{1}{N}}(x_{n}-\mu)\right]\right\}$$

1.c)
$$\frac{\sim}{2} = \frac{1}{N} \sum_{k=1}^{N} (x_{k} - \mu)(x_{k} - \mu)^{T}$$

$$A = \sum_{k=1}^{N} \sum_{k=1}^{N} (x_{k} - \mu)(x_{k} - \mu)^{T}$$

$$P(D|S) = \frac{1}{(a_{\overline{n}})^{N_{a_{\overline{n}}}}} |S^{\overline{n}}|^{N_{a_{\overline{n}}}} |$$

$$=\frac{1}{(2\pi)^{Nd/2}}\left(\frac{d}{|\Sigma|}N_{2}\left(\frac{d}{|\Sigma|}\Omega_{i}\right)\exp\left\{-\frac{N}{2}\sum_{i=1}^{d}\lambda_{i}\right\}$$

$$= \underset{\mathcal{N}_{i}}{\operatorname{arg min}} - \left(n \left[\frac{1}{(3\pi)^{nd/2} |\widetilde{\Sigma}|^{n/2}} \left(\frac{1}{|1|} \lambda i \right)^{\frac{N}{2}} \operatorname{exp} \left(-\frac{N}{2} \sum_{i=1}^{N} \lambda_{i} \right) \right]$$

$$\nabla_{\lambda} - \ln (P(D|\Sigma)) = \nabla_{\lambda} \left[-\frac{\lambda}{2} \sum_{i=1}^{d} \ln (\lambda_i) + \frac{\lambda}{2} \sum_{i=1}^{d} \lambda_i \right]$$

$$0 = \left[\left[1 - \frac{1}{\lambda_1} \right] - \frac{1}{\lambda_2} \right] \longrightarrow \mathcal{N} = \left[1 - \frac{1}{\lambda_1} \right] \longrightarrow \mathcal{N} = \left[1 - \frac{1}{\lambda_1} \right]$$

(e) Prove
$$\hat{\Sigma}_{ML} = \frac{1}{N} \sum_{n=1}^{N} (x_n - \mu)(x_n - \mu)^T = \sum_{n=1}^{N} \sum_{n=1}^{N} (x_n - \mu)(x_n -$$

$$A = \widehat{\Sigma} \widehat{\Sigma}^{-1} = I.$$

$$\widehat{\Sigma} = \widehat{\Xi} = \frac{1}{N} \widehat{\Sigma} (x_n - y_n) (x_n - y_n)^{T}.$$

If) Take derivative w.y.t to
$$\Sigma$$
, do some tedious matrix calculus, then get $\hat{\Sigma}$.

set $\frac{d(P)}{d\hat{\Sigma}} = 0$,

$$\#(\widehat{\Sigma}_{ML}) = \frac{N}{N} \Sigma + \Sigma$$

by defining
$$\hat{\mu} = \frac{1}{N} \sum_{n=1}^{N} x_n$$
 & $\hat{\Sigma}_{n} = \frac{1}{N-1} \sum_{n=1}^{N} (x_n - \hat{\mu})^T$

we can obtain an unbiased estimator of S.

- 2. See Jupyter Notebook
- 3. See Jupyter Wate book
 - 4. Currently trying to remplement NVLab's notse 2 notse using the newer version of tonsorflow. and also trying to train the neural net with different note distribution other tham gaussian & potsson. Got nothing to report yet for this intestone.