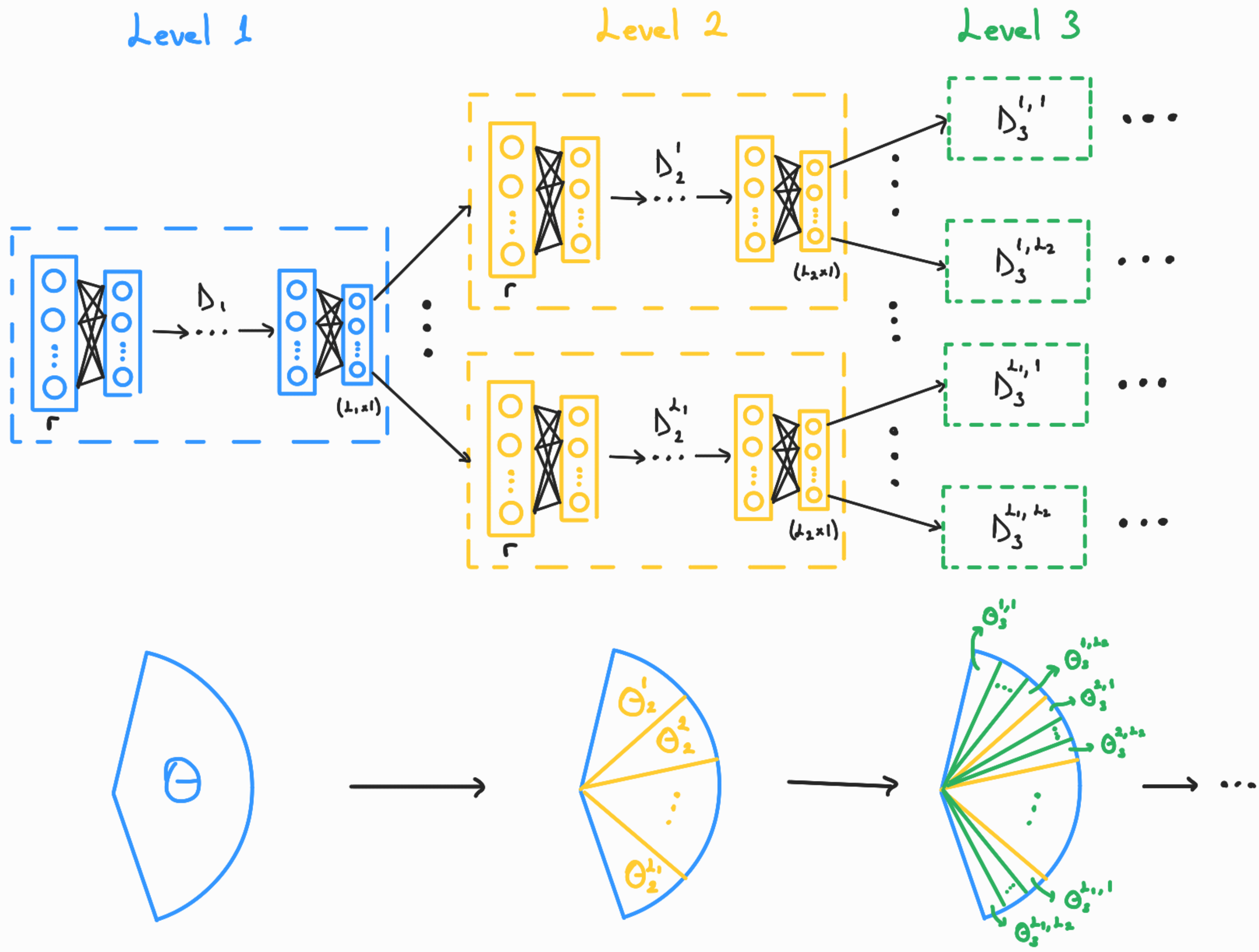
A Novel Tree Model Based DNN to Achieve a High-Resolution DOA Estimation via Massive MIMO Receive Array

The DNN Model



r : feature vector of the input signal

H : # of levels

G_h : # of fully connected MLNNs in level h where $1 \leq h \leq H$

All the G_h networks in the same level have identical structures.

Only one network in each level will be activated while performing DOA estimation.

L_h : # of output neurons in the G_h networks

$$\Rightarrow \quad G_{h+1} = G_h \cdot L_h = L_1 \cdot L_2 \cdot \dots \cdot L_{h-1} \cdot L_h \quad \text{for } 1 \leq h \leq H-1,\ G_1 = 1$$

⟹ Spatial Resolution of Level h,

$$\Delta\theta_h = \frac{\theta_{max} - \theta_{min}}{G_h L_h}$$

↳ the size of subintervals in level h

⟹ Spatial Resolution of Level H,

$$\Delta\theta_H = \frac{\theta_{max} - \theta_{min}}{G_H L_H} = \frac{\theta_{max} - \theta_{min}}{L_1 L_2 \cdots L_H}$$

⟹ The final estimated DOA $\hat{\theta}$,

$$\hat{\theta} = \theta_{min} + l^T \underbrace{\Delta\theta}_{[\Delta\theta_1 \ \Delta\theta_2 \cdots \Delta\theta_H]^T} = \theta_{min} + \sum_{h=1}^{H} \overset{1 \leq l_h \leq L_h}{l_h} \Delta\theta_h$$

Training Procedure

$$y(t) = As(t) + n(t)$$

$$R = A R_s A^H + R_n = \sum_{k=1}^{K} \sigma_k^2 \cdot [a(\theta) a^H(\theta)] + \sigma_n^2 \cdot I_{M \times M}$$

For one-input signal case, $(K = 1)$

→ $\bar{r} = [R_{1,2} \ R_{1,3} \cdots R_{1,M} \ R_{2,3} \cdots R_{2,M} \cdots \cdots R_{M-1,M}]^T, \quad r \in \mathbb{R}^{\frac{M(M-1)}{2} \times 1}$

→ $r = [Re\{\bar{r}^T\} \ Im\{\bar{r}^T\}]^T, \quad r \in \mathbb{R}^{M(M-1) \times 1}$

$z^h_{L_h \times 1}$: one-hot form label vector for training D_h.

⟶ $\|z^h\|_1 = 1, \quad z^h(l(h)) = z^h(l_h) = 1.$

$\Rightarrow$ $\{(r, z^h)\}$: training set with training data and training label

$\hat{z}^h$: output prediction vector of D_h for r

$$\longrightarrow \text{loss} = -\frac{1}{L_h} \sum_{l_h=1}^{L_h} \left[z^h(l_h) \log(\hat{z}^h(l_h)) + (1 - z^h(l_h)) \log(1 - \hat{z}^h(l_h)) \right]$$

! For $K > 1$, R is divided into $R_1, R_2, \ldots, R_K$.

$$R_1 \downarrow r_1, \quad R_2 \downarrow r_2, \quad \ldots, \quad R_K \downarrow r_K$$

r also can be written as $r = r_1 + r_2 + \cdots + r_K$

$Z^h = [z_1^h \; z_2^h \; \cdots \; z_K^h]$ where $\|z_k^h\|_1 = 1$.

$l_k = [l_{k,1} \; l_{k,2} \; \cdots \; l_{k,H}]^T$

$\hat{\theta}_k = \theta_{min} + l_k^T \Delta\theta = \theta_{min} + \sum_{h=1}^{H} l_{k,h} \cdot \Delta\theta_h$