Elastic Weight Consolidation (EWC)

🎯 EWC Weight Importance Mechanism

Task A (Previous Task)
Weight Importance:

⬤⬤⬤ High (Fixed) ⬤⬤ Low

Fisher Information
Matrix F

Task B (New Task)
Learning Constraints:

⬤⬤ Constrained ⬤⬤ Free

📐 EWC Loss Function

$$L_{total} = L_{new} + \lambda \cdot L_{EWC}$$

New task loss + Important weight preservation penalty = Balanced learning

✨ Effects
✓ 중요 지식 보존
✓ 유연한 학습
✓ 메모리 효율적
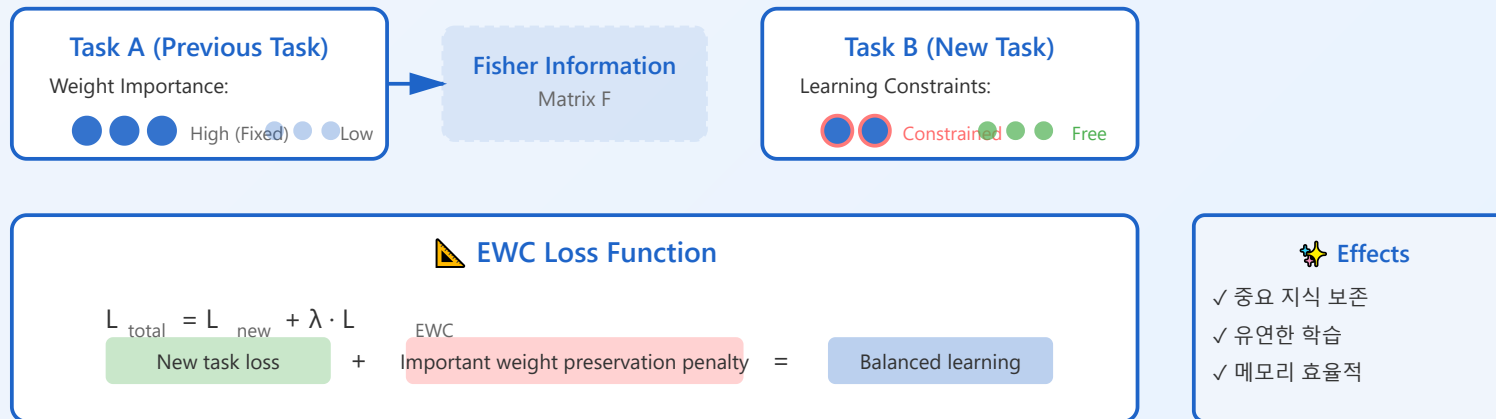
🎯 EWC Mechanism

- Fisher Information Matrix: Identify important weights

- Weight importance calculation: Identify parameters important to previous tasks

- Add constraints: Limit important weight changes

- Maintain flexibility: Freely update less important weights

📐 Loss Function

- L_total = L_new + λ * L_EWC

- L_EWC = Σ F_i * (θ_i - θ*_i)^2

- F_i: Fisher information (weight importance)

- λ: Regularization strength (typically 1-1000)

⚡ Penalty Application

- High penalty for important weight changes

- Freely learn less important weights

- Cumulative penalty across multiple tasks

- Memory efficient: Store only Fisher matrix