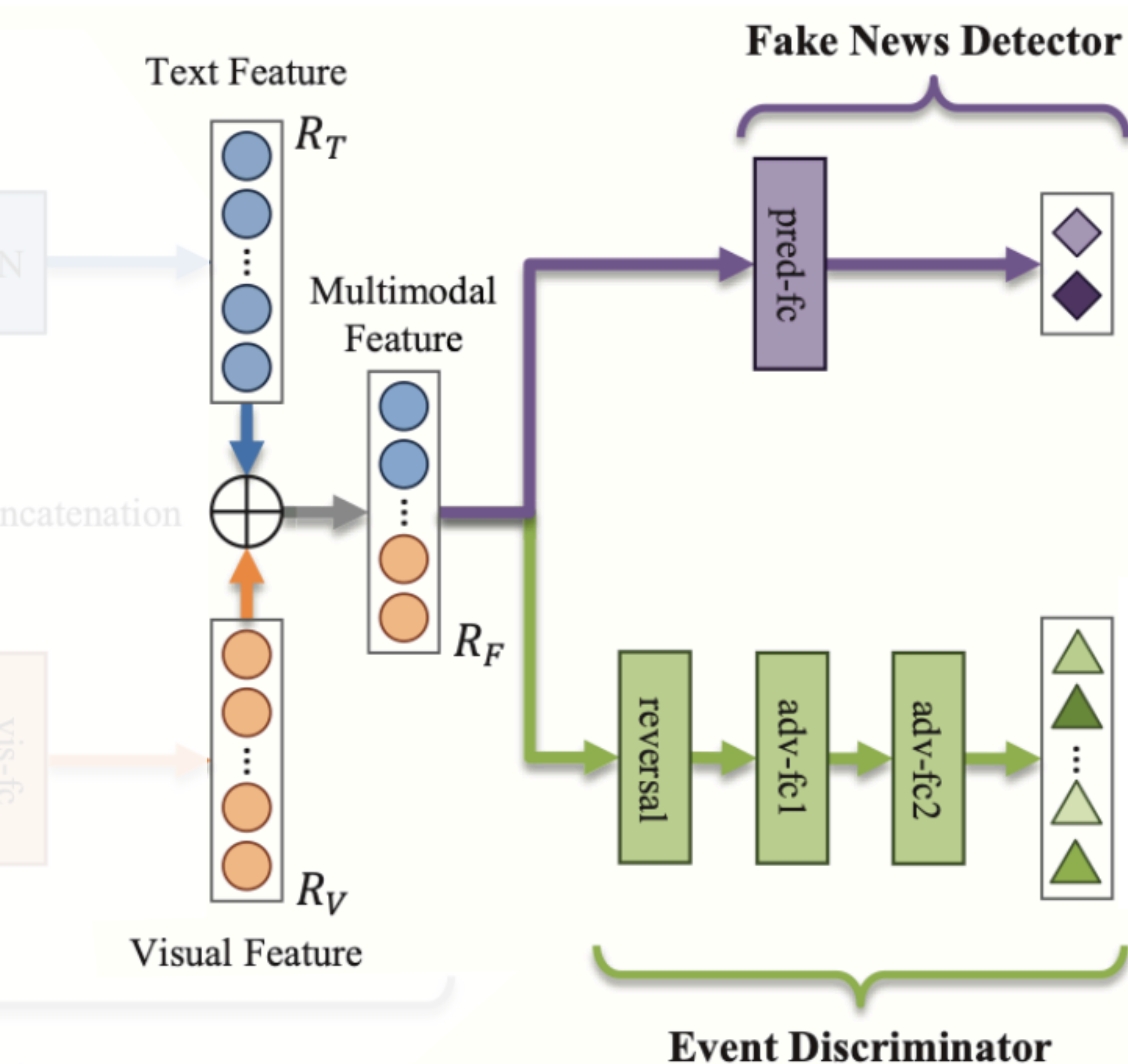


# Methodology.....

## Model Integration



- parameter set we seek is the saddle point of the final objective function, use SGD to solve problem:
  - $(\hat{\theta}_f, \hat{\theta}_d) = \arg \min_{\theta_f, \theta_d} L_{final}(\theta_f, \theta_d, \hat{\theta}_e)$
  - $\hat{\theta}_e = \arg \max_{\theta_e} L_{final}(\hat{\theta}_f, \hat{\theta}_d, \theta_e)$
- Here adopt the gradient reversal layer (GRL)
  - Acts as an identity function during forward stage, and it multiplies gradient with  $-\lambda$  and passes the results to the preceding layer during back-prop stage.
  - GRL easily added between  $G_f(\cdot; \theta_f)$  and  $G_e(\cdot; \hat{\theta}_e)$

# Methodology.....

## Gradient Reversal Layer

**Input:** The multi-modal input  $\{m_i\}_{i=1}^N$ , the auxiliary event label  $\{e_i\}_{i=1}^N$ , the detection label  $\{y_i\}_{i=1}^N$  and the learning rate  $\eta$

1. for number of training iterations do

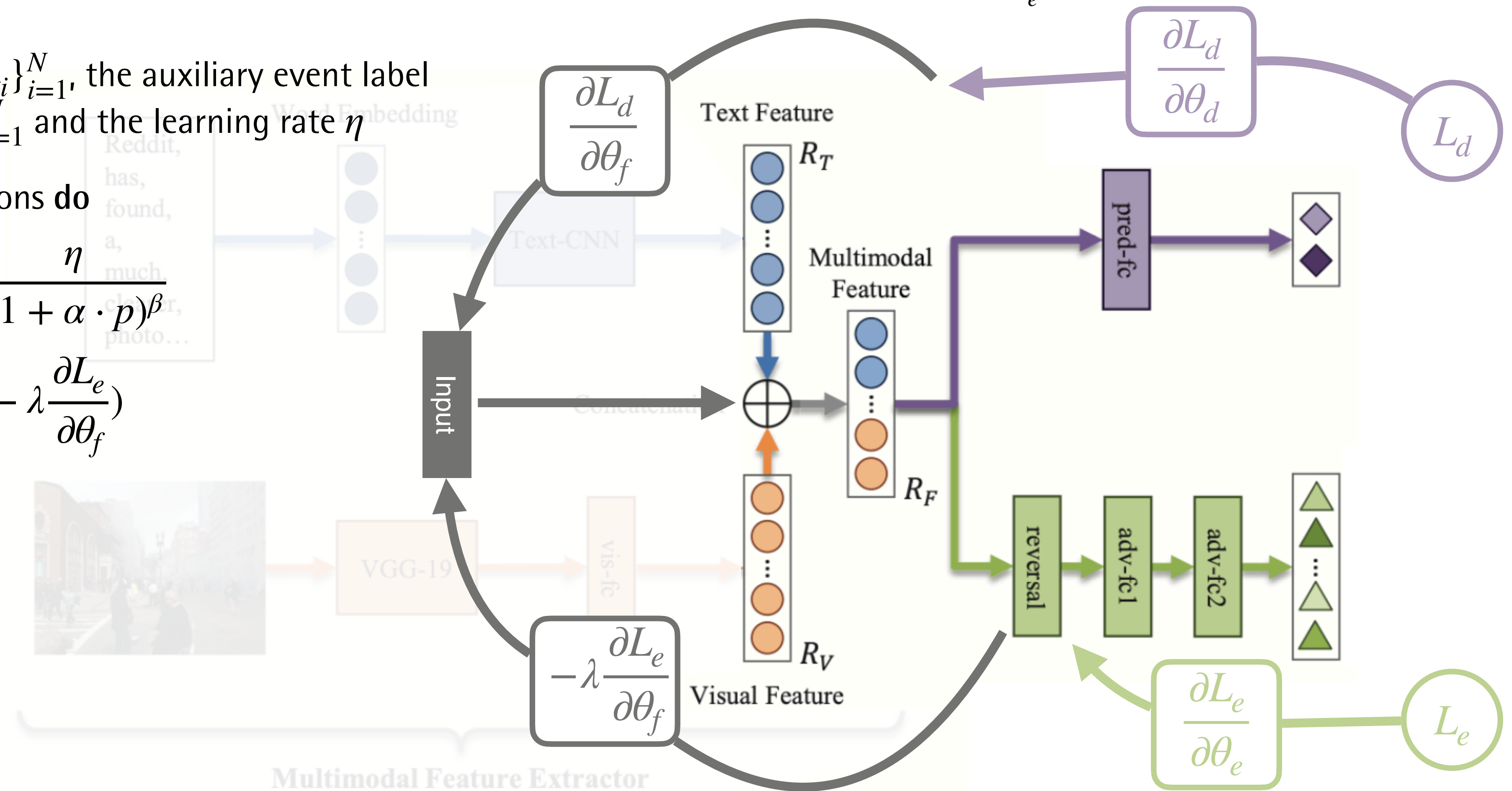
2. Decay learning rate:  $\eta' = \frac{\eta}{(1 + \alpha \cdot p)^\beta}$

3. Update  $\theta_f \leftarrow \theta_f - \eta' \left( \frac{\partial L_d}{\partial \theta_f} - \lambda \frac{\partial L_e}{\partial \theta_f} \right)$

4. Update  $\theta_e \leftarrow \theta_e - \eta' \frac{\partial L_e}{\partial \theta_e}$

5. Update  $\theta_d \leftarrow \theta_d - \eta' \frac{\partial L_d}{\partial \theta_d}$

6. end for



- $L_{final}(\theta_f, \theta_d, \theta_e) = L_d(\theta_f, \theta_d) - \lambda L_e(\theta_f, \theta_e)$
- $(\hat{\theta}_f, \hat{\theta}_d) = \arg \min_{\theta_f, \theta_d} L_{final}(\theta_f, \theta_d, \hat{\theta}_e)$
- $\hat{\theta}_e = \arg \max_{\theta_e} L_{final}(\hat{\theta}_f, \hat{\theta}_d, \theta_e)$