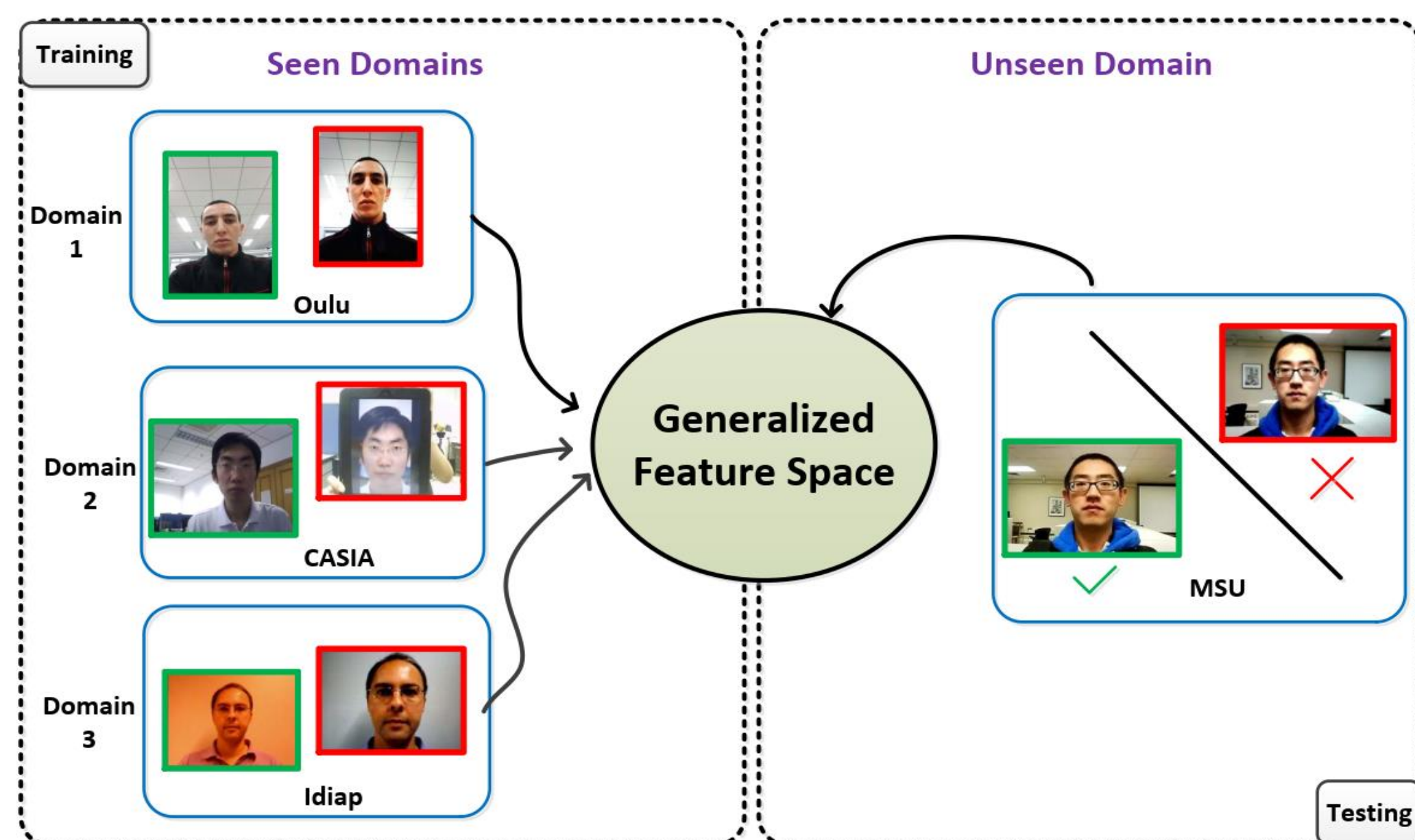
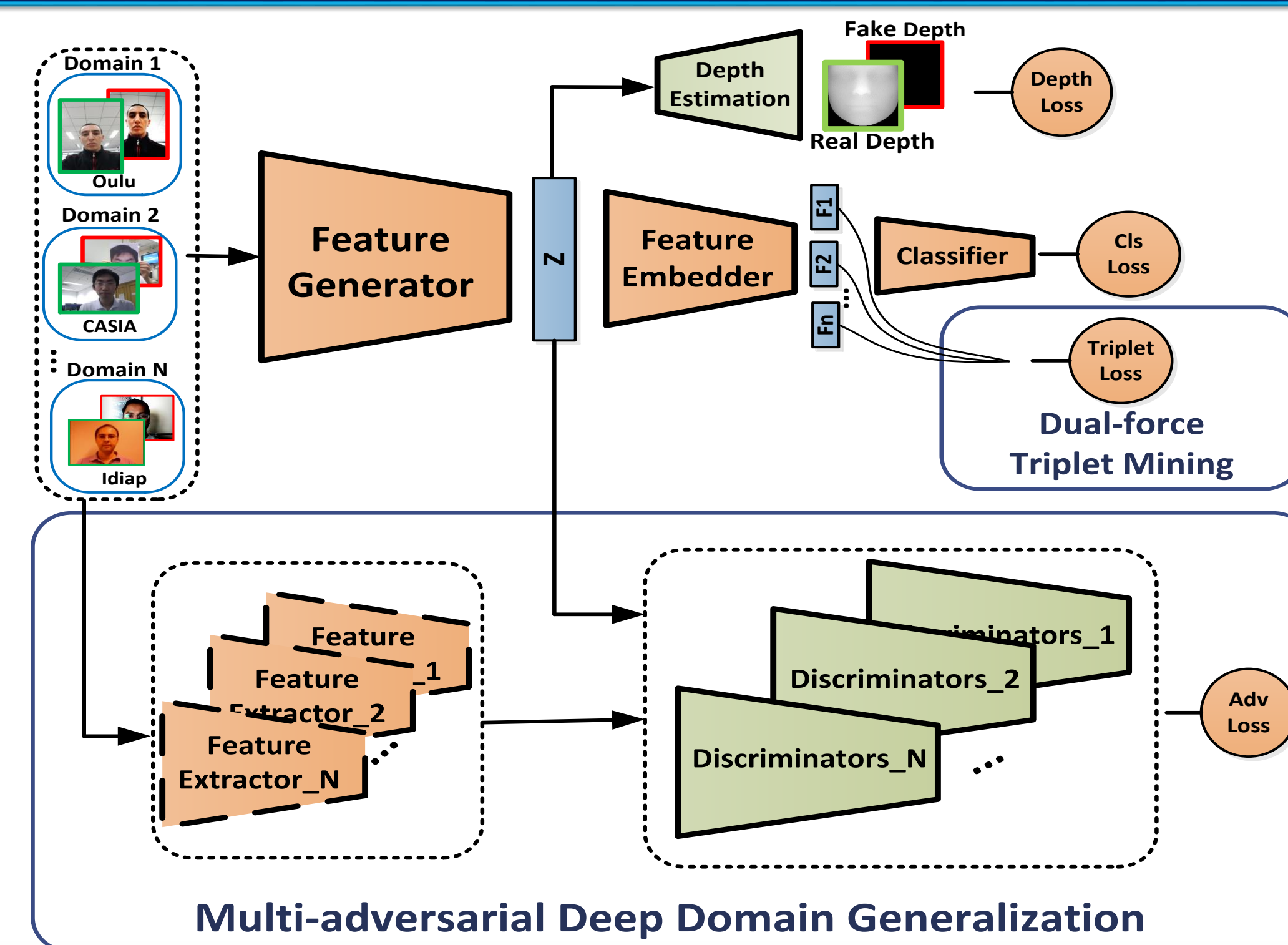


Introduction



- Improving the generalization ability of face anti-spoofing methods from the perspective of the domain generalization.
- Learning a generalized feature space that is shared and discriminative.

Framework



$$\min_{G,E,C,Dep} \max_{D_1,D_2,\dots,D_N} \mathcal{L}_{MADDG} = \mathcal{L}_{DG} + \mathcal{L}_{Trip} + \mathcal{L}_{Dep} + \mathcal{L}_{Cls}$$

Experimental Results

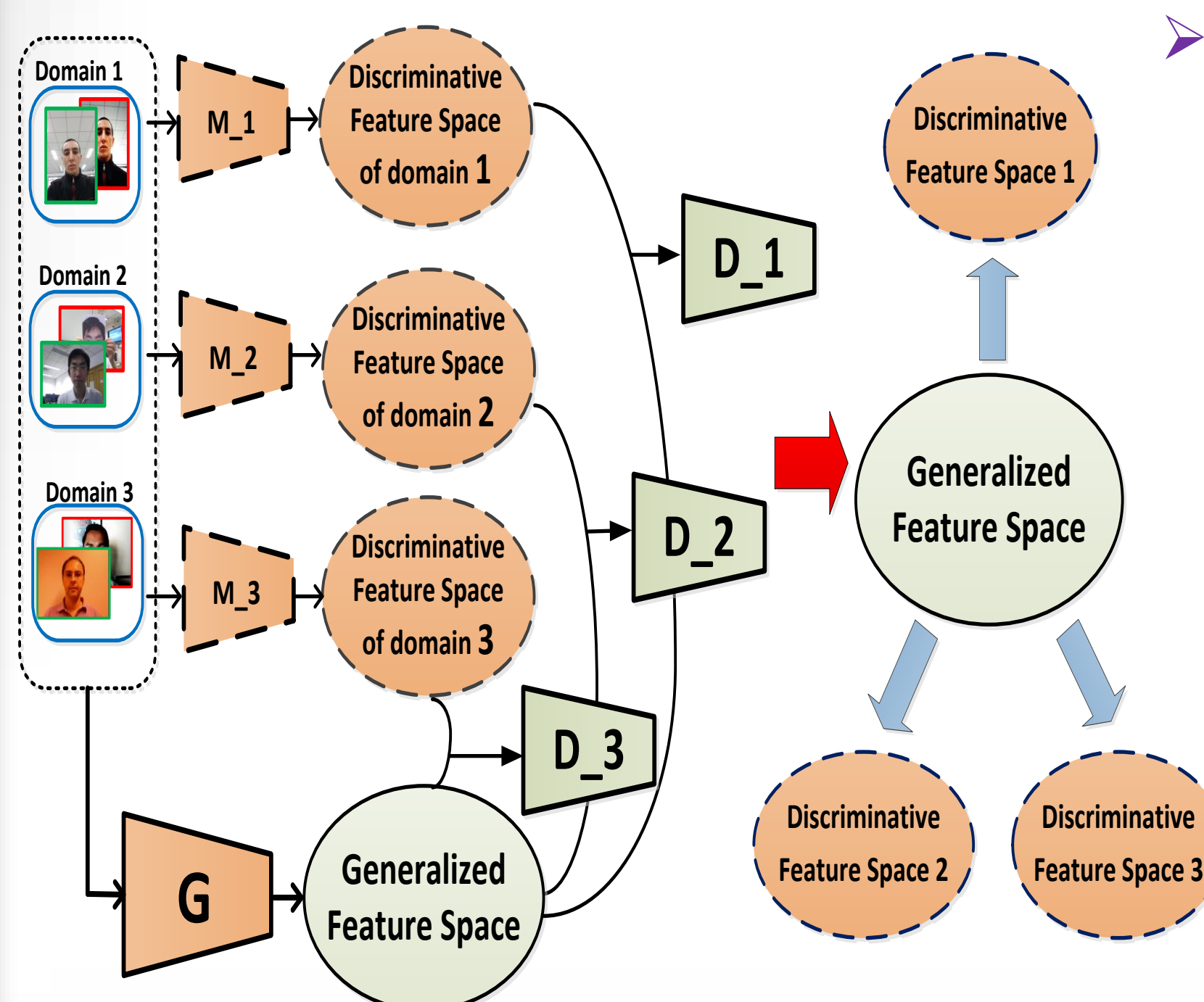
Datasets



Comparison Results

| Methods | O&C&I to M | | O&M&I to C | | O&C&M to I | | I&C&M to O | |
|------------------|--------------|--------------|-------------|--------------|--------------|--------------|--------------|--------------|
| | HETR | AUC | HETR | AUC | HETR | AUC | HETR | AUC |
| MS_LBP | 29.76 | 78.50 | 54.28 | 44.98 | 50.30 | 51.64 | 50.29 | 49.31 |
| B_CNN | 29.25 | 82.87 | 34.88 | 71.94 | 34.47 | 65.88 | 29.61 | 77.54 |
| IDA | 66.67 | 27.86 | 55.17 | 39.05 | 28.35 | 78.25 | 54.20 | 44.59 |
| CT | 28.09 | 78.47 | 30.58 | 76.89 | 40.40 | 62.78 | 63.59 | 32.71 |
| LBPTOP | 36.90 | 70.80 | 42.60 | 61.05 | 49.45 | 49.54 | 53.15 | 44.09 |
| Auxiliary(Depth) | 22.72 | 85.88 | 33.52 | 73.15 | 29.14 | 71.69 | 30.17 | 77.61 |
| MMD_AAE | 27.08 | 83.19 | 44.59 | 58.29 | 31.58 | 75.18 | 40.98 | 63.08 |
| Ours | 17.69 | 88.06 | 24.5 | 84.51 | 22.19 | 84.99 | 27.98 | 80.02 |

Network Components

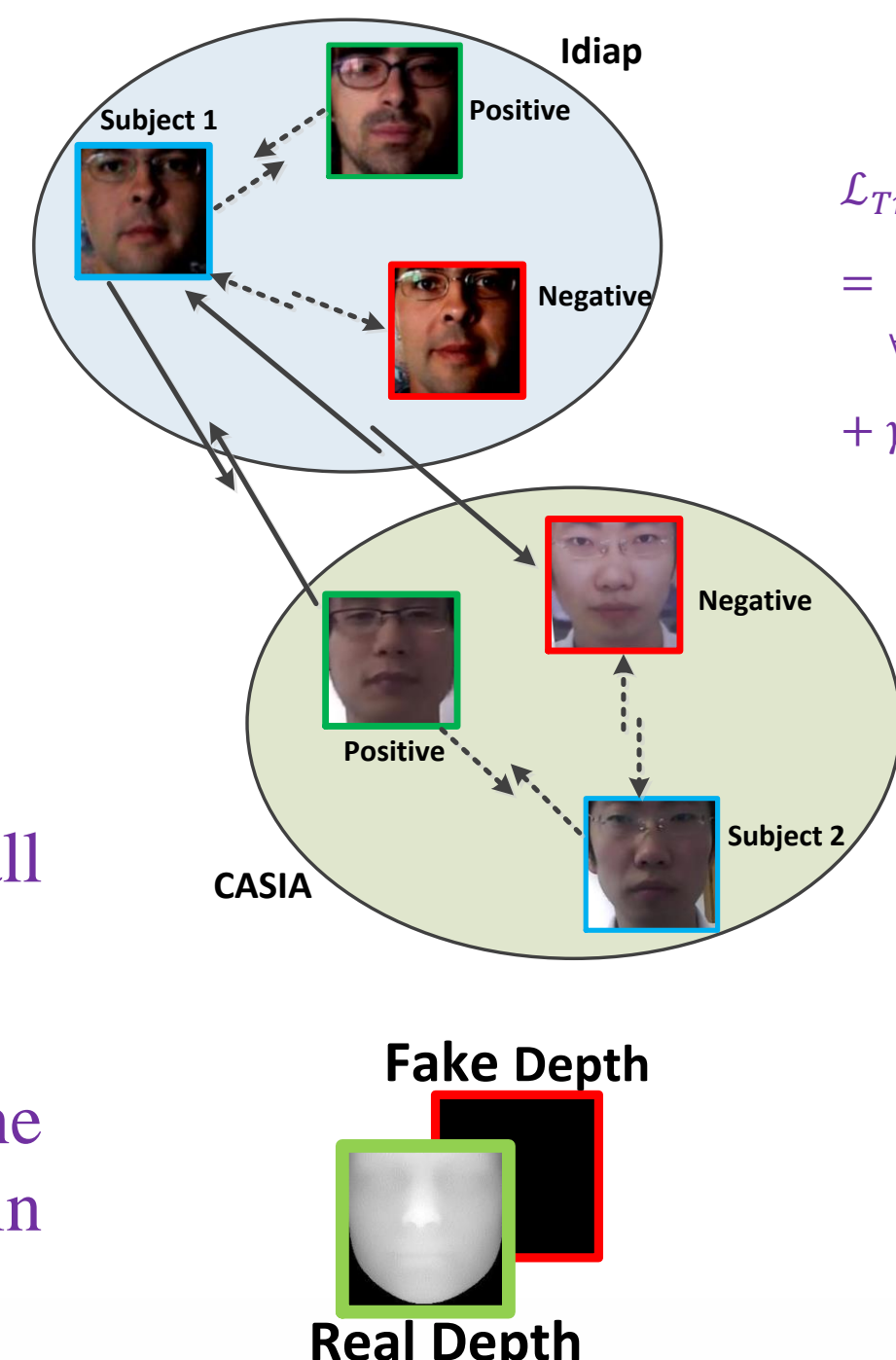


Multi-adversarial Domain Generalization :

$$\mathcal{L}_{DG} = (\mathbf{X}, \mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_N; G, D_1, D_2, \dots, D_N)$$

$$= \sum_{i=1}^N \left(\mathbb{E}_{x \sim \mathbf{X}} [\log(D_i(G(x)))] + \mathbb{E}_{x_i \sim \mathbf{X}_i} [\log(1 - D_i(M_i(x_i)))] \right)$$

- Train one feature generator to compete with all the N domain discriminators simultaneously.
- A shared feature space is learned after one feature generator fools all the N domain discriminators.



Dual-force Triplet-mining Constraint

$$\mathcal{L}_{Trip} = (\mathbf{X}, \mathbf{Y}; G, E)$$

$$= \sum_{\forall y_a=y_p, \forall y_a \neq y_n, i=j} \left[\|E(G(x_i^a)) - E(G(x_j^p))\|_2^2 - \|E(G(x_i^a)) - E(G(x_j^n)) + \alpha_1\|_2^2 \right]_+$$

$$+ \gamma \sum_{\forall y_a=y_p, \forall y_a \neq y_n, i \neq k} \left[\|E(G(x_i^a)) - E(G(x_k^p))\|_2^2 - \|E(G(x_i^a)) - E(G(x_k^n)) + \alpha_2\|_2^2 \right]_+$$

- Fake face with the same identity has similar facial characteristics; real face with the different identity has different facial characteristics.
- Distance of each subject to its intra/cross-domain positive smaller than to its intra/cross-domain negative.

Auxiliary Face Depth Information

$$\mathcal{L}_{Dep}(X; Dep) = \|Dep(G(X)) - I\|_2^2$$

- Feature space guided to exploit generalized differentiation cues related to the face depth in the learning process.

Ablation Study

| Methods | O&C&M to I | |
|--------------|--------------|--------------|
| | HETR | AUC |
| Ours_wo/mgan | 36.50 | 63.15 |
| Ours_wo/trip | 34.99 | 71.37 |
| Ours_wo/dep | 37.44 | 62.82 |
| Ours | 22.19 | 84.99 |

Limited source domains

| Methods | M&I to C | | M&I to O | |
|---------|--------------|--------------|--------------|--------------|
| | HETR | AUC | HETR | AUC |
| MS_LBP | 51.16 | 52.09 | 43.63 | 58.07 |
| IDA | 45.16 | 58.8 | 54.52 | 42.17 |
| LBPTOP | 45.27 | 54.88 | 47.26 | 50.21 |
| Ours | 41.02 | 64.33 | 39.35 | 65.10 |

Attention Map

