# Privacy Attributes-aware Message Passing Neural Network for Visual Privacy Attributes Classification

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**Task**: Visual Privacy Attributes Classification

**Labels:**
Partial Face
Race
Skin Color
Approximate Age
Approximate Weight
Occupation
Gender
Eye Color
Social Circle
Professional Circle
Hair Color
Complete Face

**Challenges**:

| Tasks | Input | Output (10 classes) | Output Space |
|---|---|---|---|
| Single-label Classification | Image | $[0, 0, 0, 0, 0, \mathbf{1}, 0, 0, 0, 0]$ | $\mathbf{10}$ |
| Multi-label Classification | Image | $[\mathbf{1}, 0, \mathbf{1}, 0, 0, \mathbf{1}, 0, 0, \mathbf{1}, \mathbf{1}]$ | $\mathbf{2^{10}}$ |

**Solutions**: Reduce the output space

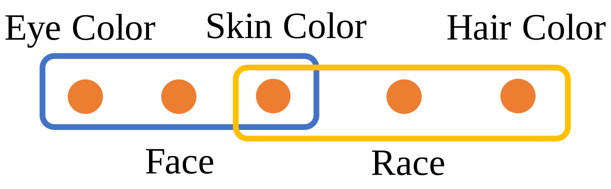
$$[\mathbf{1}, 0, \mathbf{1}, 0, 0, \mathbf{1}, 0, 0, \mathbf{1}, \mathbf{1}] \longrightarrow 2^{10}$$

$$[\mathbf{1}, 0, \mathbf{1}, 0, 0, \mathbf{1}, 0, 0, \mathbf{1}, \mathbf{1}] \longrightarrow 2^{6}$$

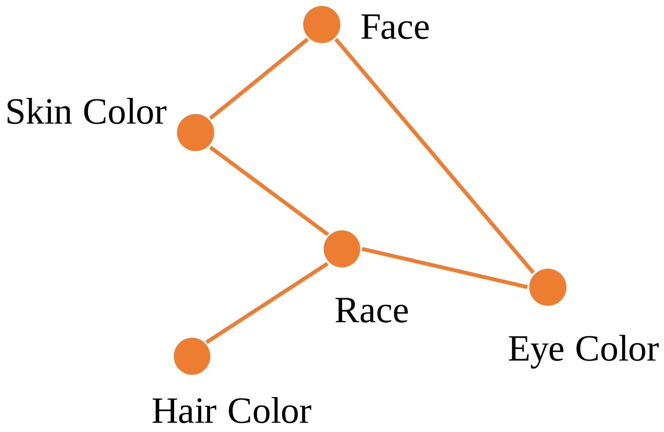
**Related Works**:

- Combining a set of labels [5]
- Class hierarchy [6]
- Embedding high dimension label vector to low dimension label vector [7]

**Dependencies between privacy attributes**




Group Dependency




Structural Dependency

**How to capture the structural dependency**?

**Message Passing Neural Network [8] (MPNN):**

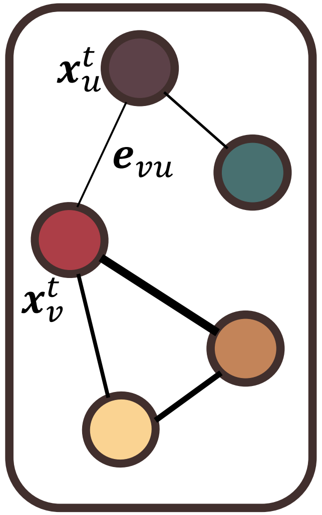
**Main Idea**: Privacy Attributes → Nodes on Graph

MPNN: Use adjacent node features to update node features.

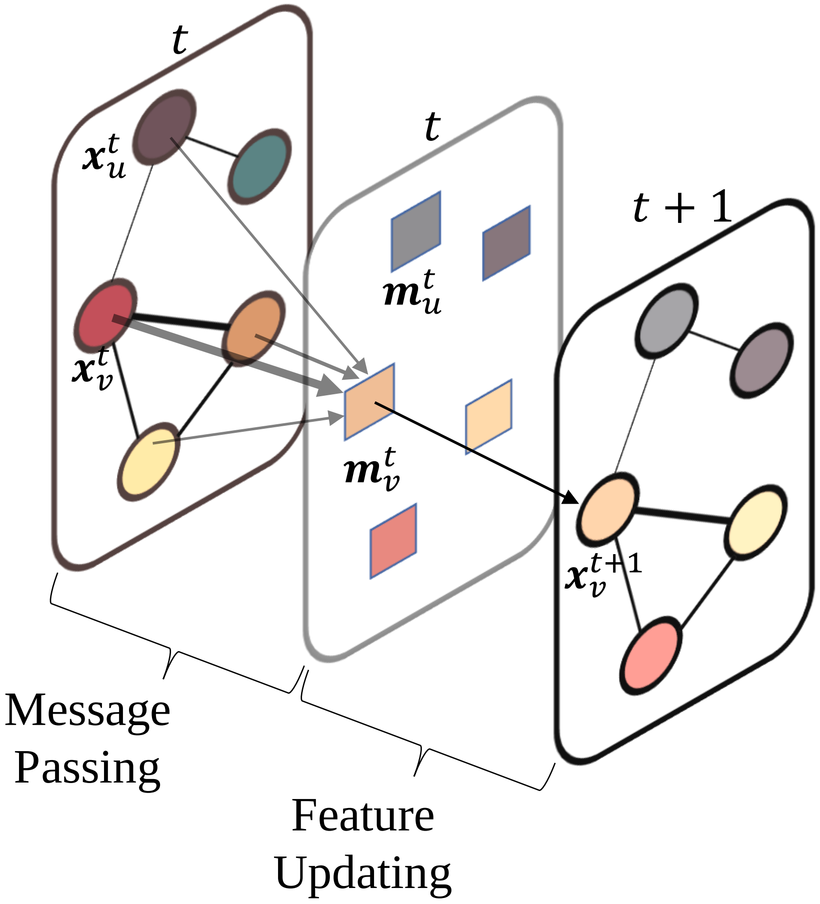
In layer $t$:

- Message Passing $\boldsymbol{m}_v^t = \sum_{u \in N(v)} M_t(\boldsymbol{x}_v^t, \boldsymbol{x}_u^t, \boldsymbol{e}_{vu})$
- Feature Updating $\boldsymbol{x}_v^{t+1} = U_t(\boldsymbol{x}_v^t, \boldsymbol{m}_v^t)$

$\boldsymbol{x}_v^t$: Feature of node $v$ in layer t
$\boldsymbol{e}_{\mathrm{vu}}$: Feature between node $v$ and $u$
$\boldsymbol{m}_v^t$: Hidden State of node $v$ in layer t

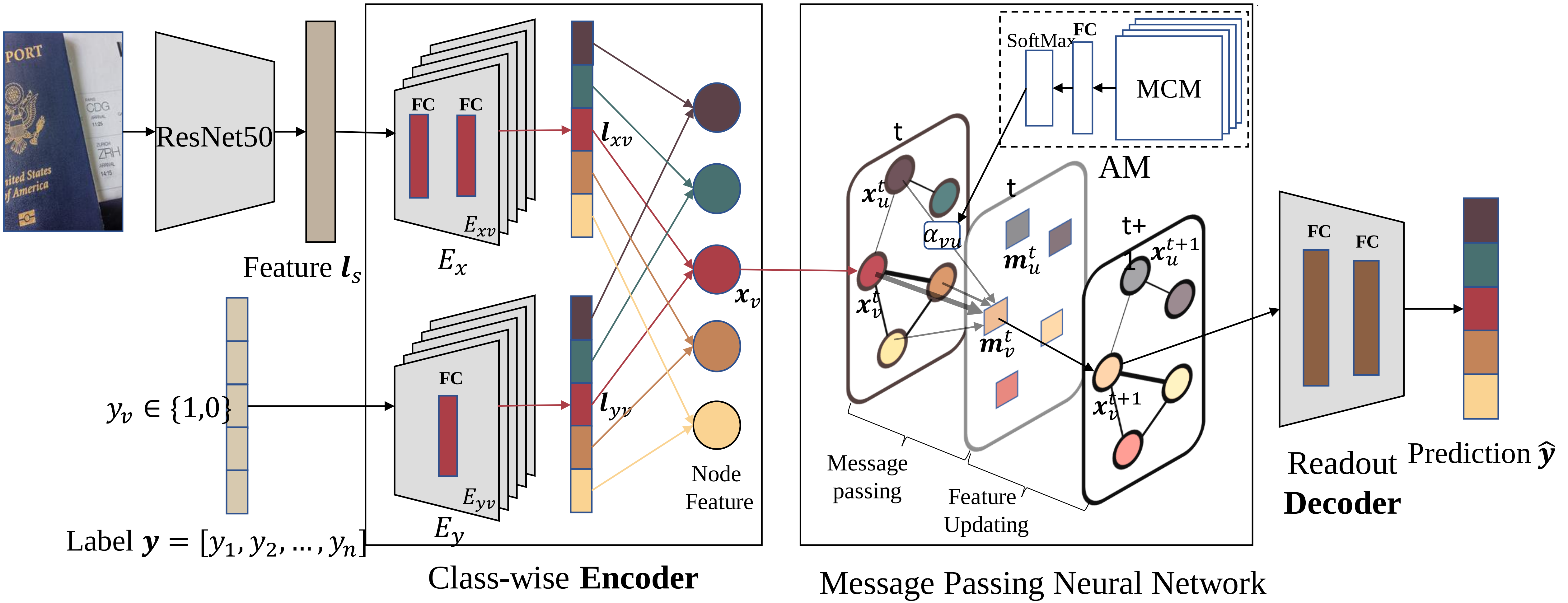



Graph




MPNN Mechanism

## Privacy Attributes-aware Message Passing Neural Network (PA-MPNN):



## Experiments:

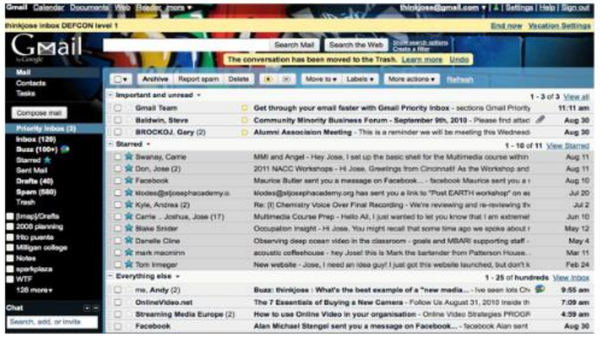
- Dataset:

  Privacy Attributes Dataset[1] with **22,167** images and **68** visual privacy attributes

- Comparison Results:

| Methods | CaffeNet [1] | GoogleNet [1] | ResNet-50 [1] | ours |
|---|---|---|---|---|
| mAP | 42.99 | 43.29 | 47.45 | **49.93** |

- Prediction Examples:




Full Name, Email Content, Email Address

Full Name, Email Content

Full Name, Email Content, **Email Address**

Race, Skin Color, Age, Occupation, Gender, Professional Circle, Hair Color, Complete Face, Partial Face, Weight, Height, Eye Color

Race, Skin Color, Age, Occupation, Gender, Professional Circle, Hair Color, Complete Face, Partial Face, Weight

Race, Skin Color, Age, Occupation, Gender, Professional Circle, Hair Color, Complete Face, Partial Face, Weight, **Height, Eye Color**


Passport, Nationality

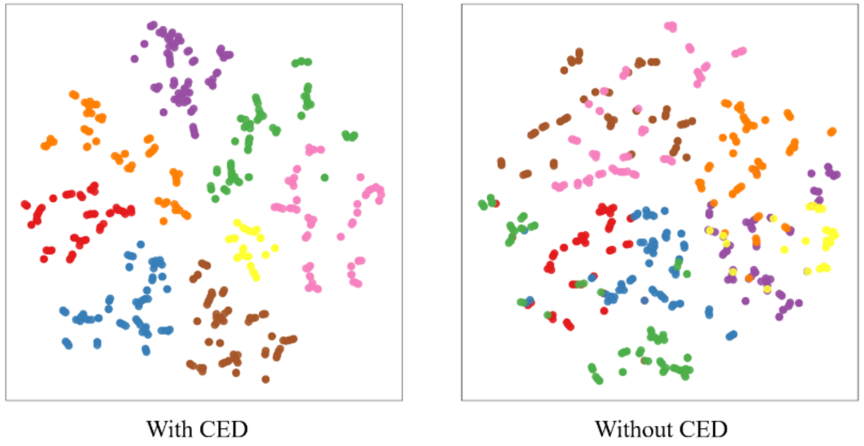
Passport

Passport, **Nationality**

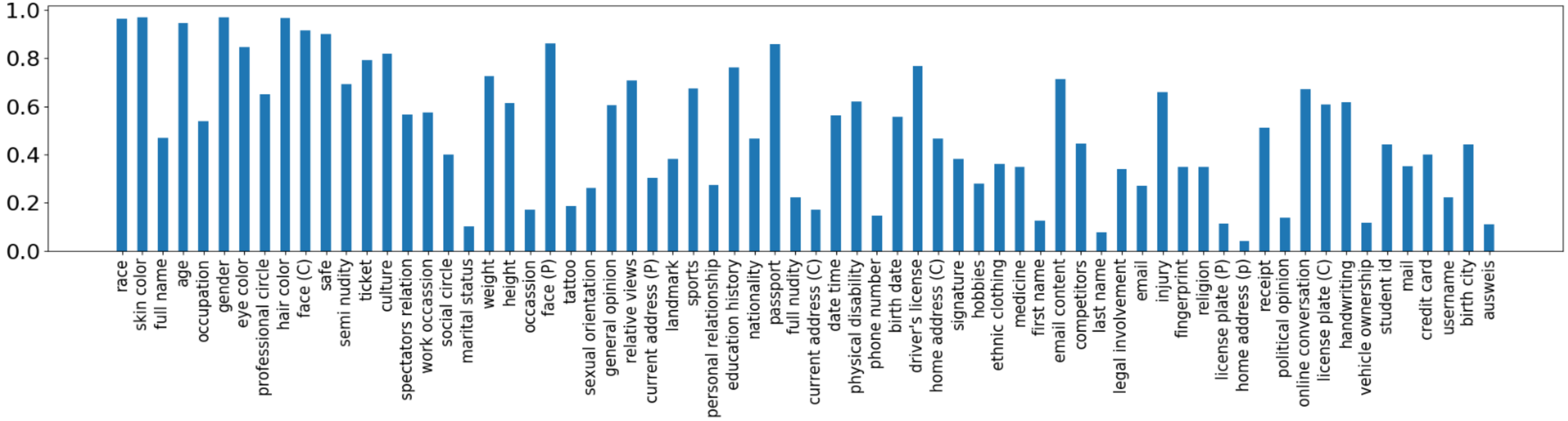
# Ablation Study:

| CED | Att. | MCM | mAP | miF1 | maF1 |
|---|---|---|---|---|---|
| | √ | √ | 49.83 | 0.7725 | 0.4428 |
| √ | | √ | 49.78 | 0.7645 | 0.4384 |
| √ | √ | | 49.78 | 0.7683 | 0.4284 |
| √ | √ | √ | **49.93** | **0.7751** | **0.4456** |

Comparison of our methods




t-SNE visualization




Average Precision scores on all visual privacy attributes. (C) represents ’complete’. (P) represents ’partial’.

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Thank you

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Please email me if you have any questions.

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