Mitigating Information Leakage in Image Representations: A Maximum Entropy Approach

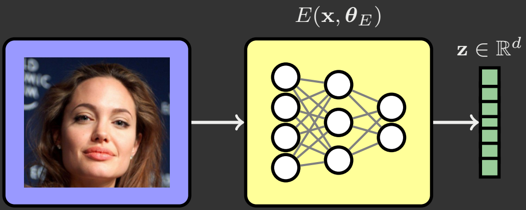
Proteek Roy and Vishnu Boddeti

Michigan State University

CVPR 2019

>>> Representation Learning: The Bright Side

* Deep Embeddings:



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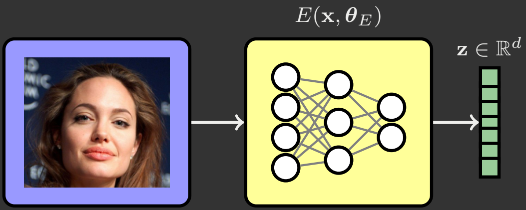

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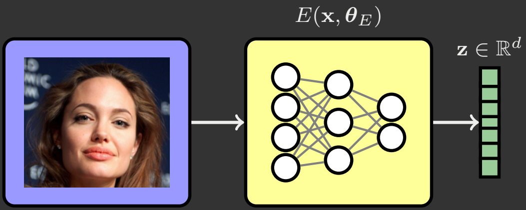

* Features contain a lot of information
  * basis for generalizing and transferring to other tasks

* Applications include:

Figure: Face Recognition

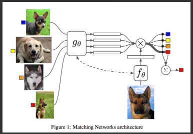

Figure: Image Retrieval

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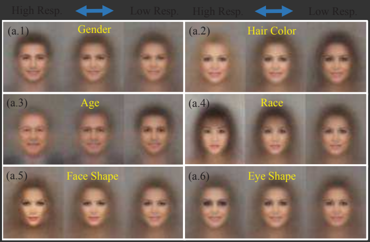
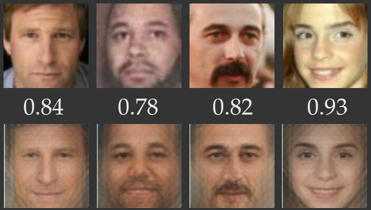
* Soft attribute from face features



Liu et al., ICCV 2015

* Reconstruction from face features



Mai et al., PAMI 2018

>>> Central Aim of This Paper

Mitigating Information Leakage

Develop representation learning algorithms that can *intentionally* and *permanently* obscure sensitive information while retaining task dependent information.

>>> Problem Setting: Adversarial Representation Learning

* Three player zero-sum game between:

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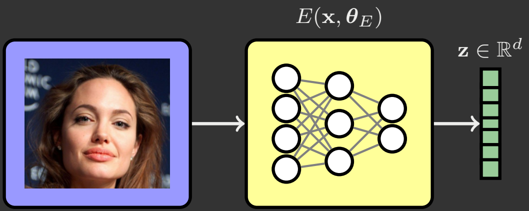

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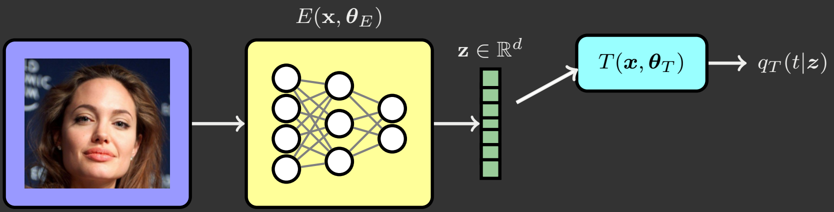

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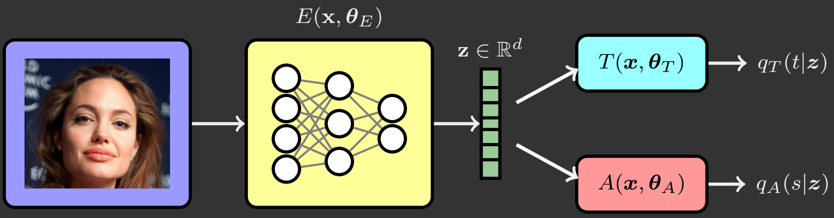

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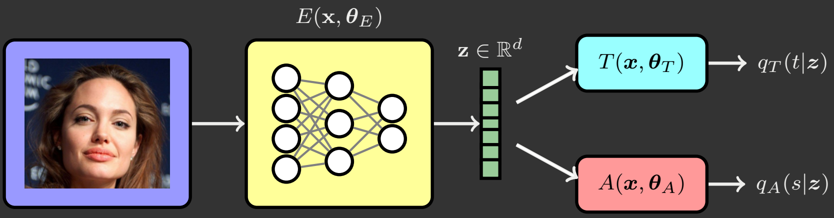

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* Minimum Likelihood Adversarial Representation Learning:

$$\min_{\boldsymbol{\theta}_E, \boldsymbol{\theta}_T} \max_{\boldsymbol{\theta}_A} \underbrace{J_1(\boldsymbol{\theta}_E, \boldsymbol{\theta}_T)}_{\text{likelihood of predictor}} - \alpha \underbrace{J_2(\boldsymbol{\theta}_E, \boldsymbol{\theta}_A)}_{\text{likelihood of adversary}} \tag{1}$$

>>> Optimizing Likelihood Can be Sub-Optimal

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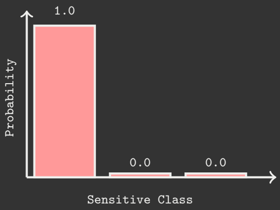

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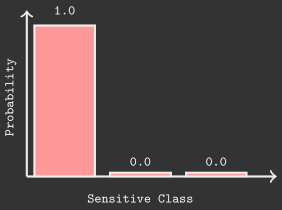

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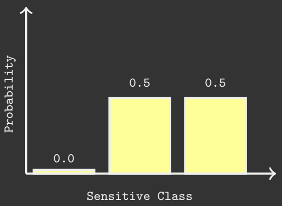

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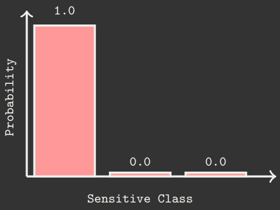

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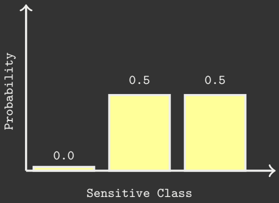

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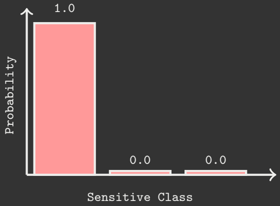

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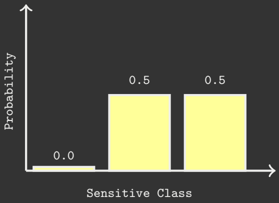

* Equillibrium

Limitations:

* Encoder target distribution leaks information !!
* Practice: simultaneous SGD does not reach equilibrium
* Class Imbalance: likelihood biases solution to majority class

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Key Idea

Optimize the encoder to maximize entropy of adversary as opposed to minimizing its likelihood.

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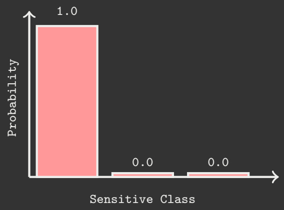

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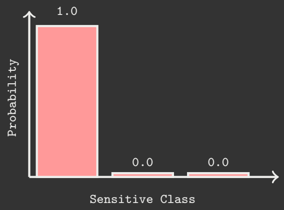

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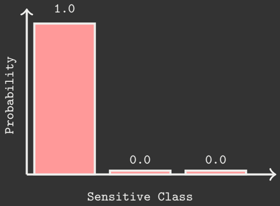

* Encoder

* Equilibrium

>>> MaxEnt-ARL Properties

* Theoretical
  * Three player non-zero sum game
  * At equilibrium, encoder induces uniform distribution in adversary when $s \perp\!\!\!\perp t$
  * Obtain conditions for stability of solution around equillibrium through linearization.

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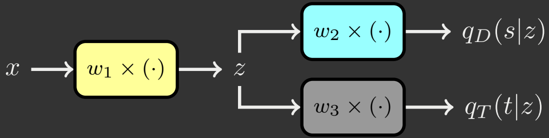
* Theoretical
  * Three player non-zero sum game
  * At equilibrium, encoder induces uniform distribution in adversary when $s \perp\!\!\!\perp t$
  * Obtain conditions for stability of solution around equillibrium through linearization.
* Practical
  * Semi-Supervised Mode: encoder does not need sensitive labels
  * Less susceptible to class imbalance than ML-ARL

>>> Three Player Game: Linear Case



* Each entity is linear scalar multiplication
* Global solution is $(w_1, w_2, w_3) = (0, 0, 0)$

Minimum Likelihood

Maximum Entropy

>>> Numerical Experiments: Fair Classification

* UCI Datatset: Creditworthiness Prediction

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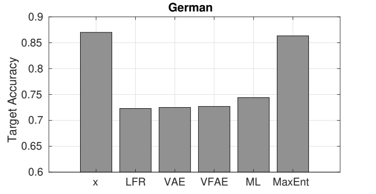

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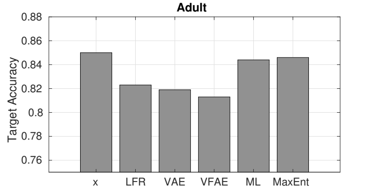

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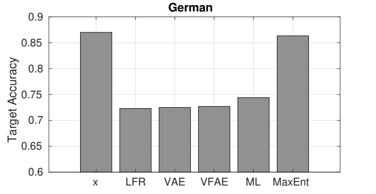
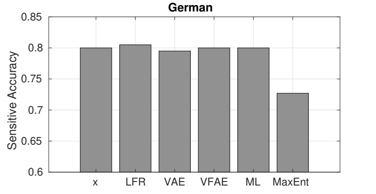


Adversary: Gender Prediction



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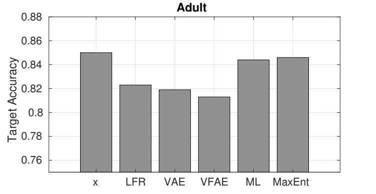

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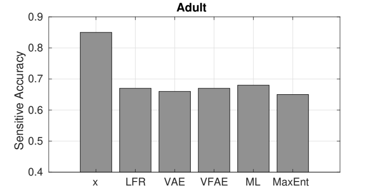

[~]$ _

>>> Numerical Experiments: Extended Yale B Faces

* 38 identities and 5 illumination directions
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* Sensitive: Illumination Label

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Method	s (lighting)	t (identity)
LR	96	78
NN + MMD (NIPS 2014)	-	82
VFAE (ICLR 2016)	57	85
ML-ARL (NIPS 2017)	57	89
Maxent-ARL	40	89

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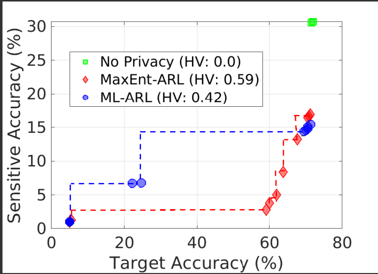

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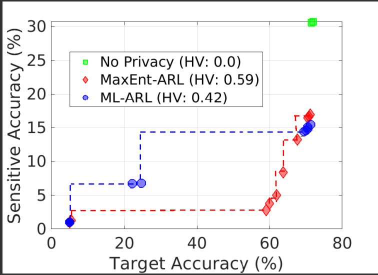

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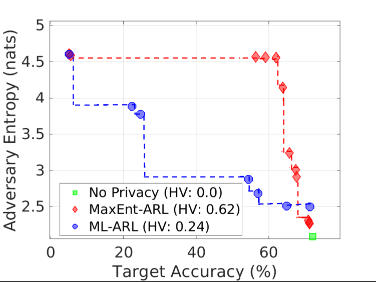

Trade-Off: Entropy

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Code:

https://github.com/human-analysis/MaxEnt-ARL.git

More Details: Poster # 175