# DAPter: Preventing User Data Abuse in Deep Learning Inference Services

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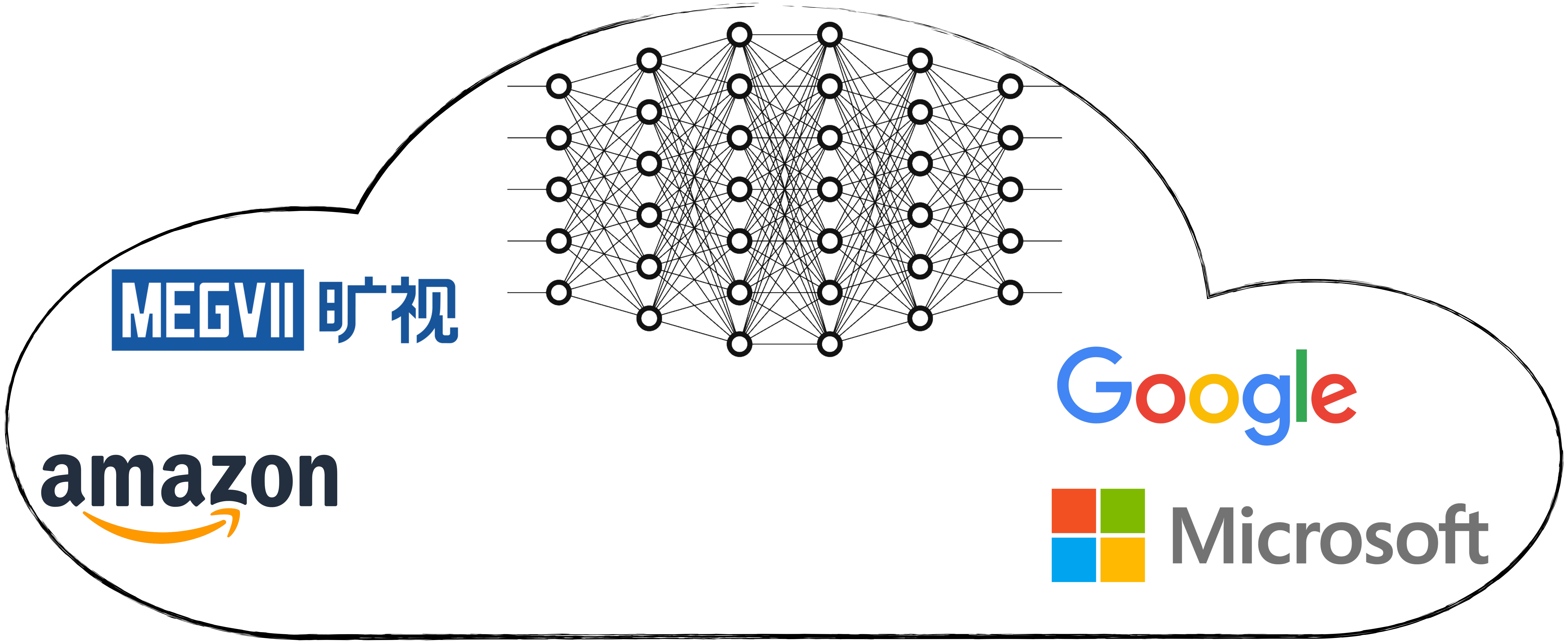
# DLIS Scenario

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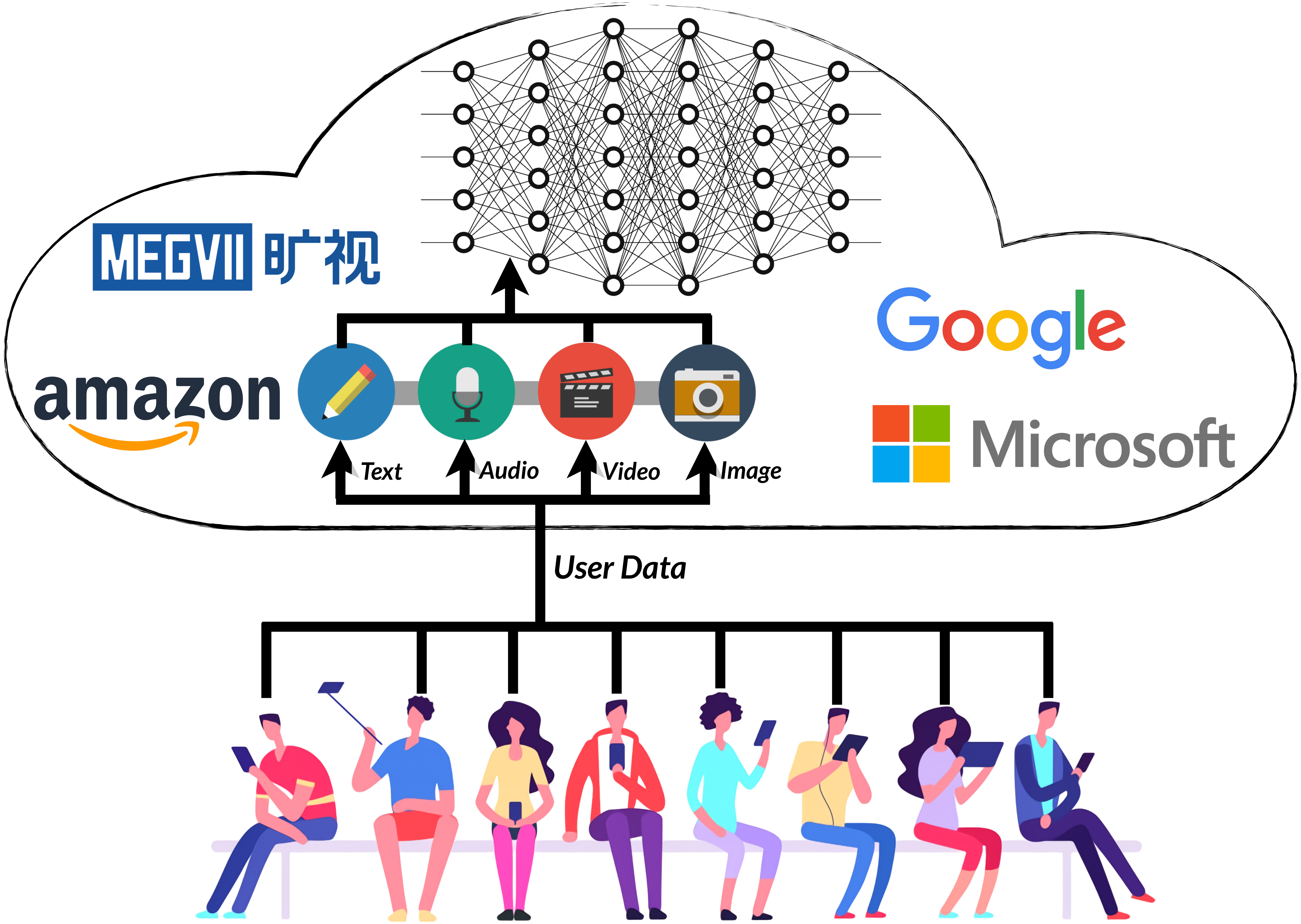

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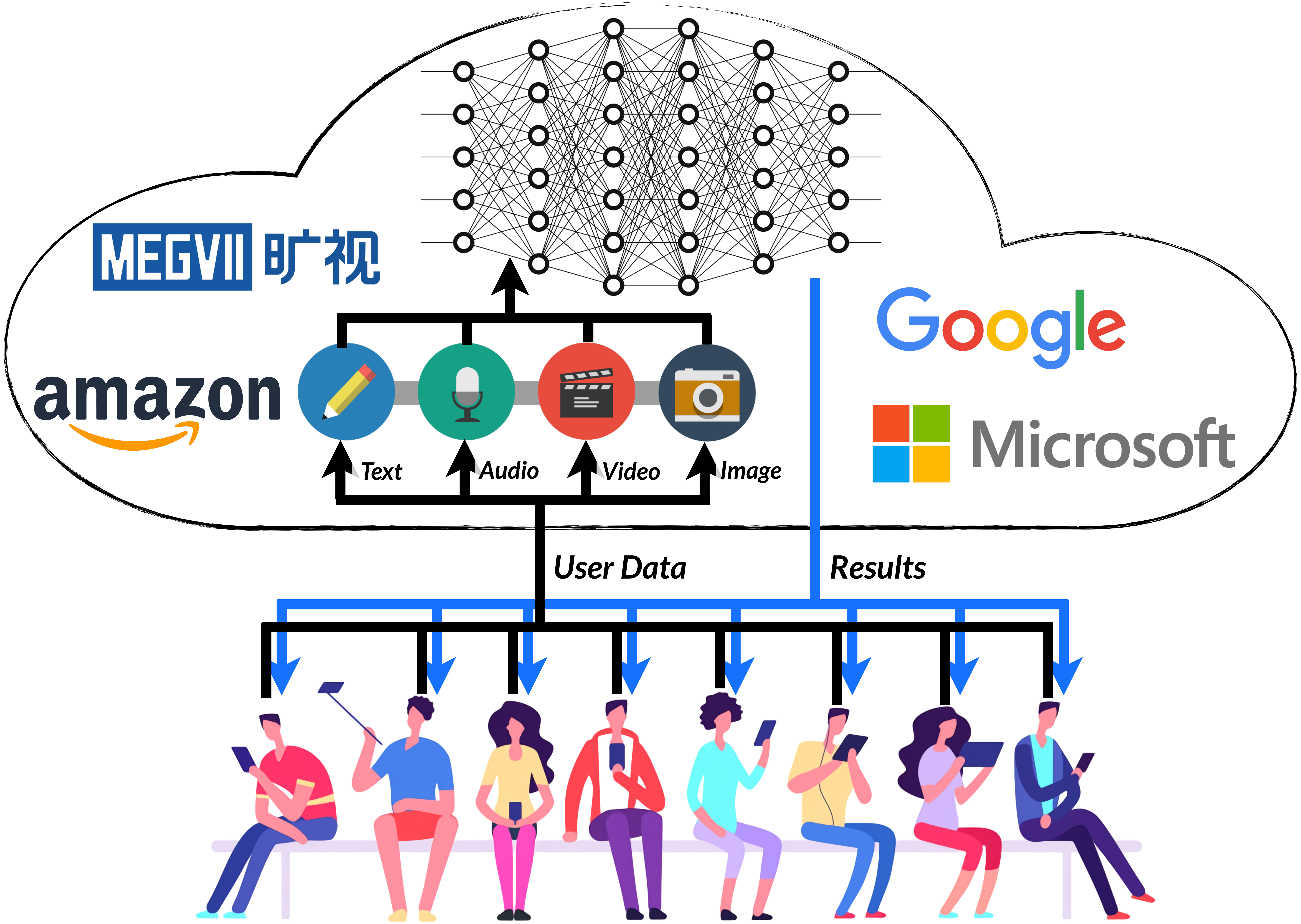

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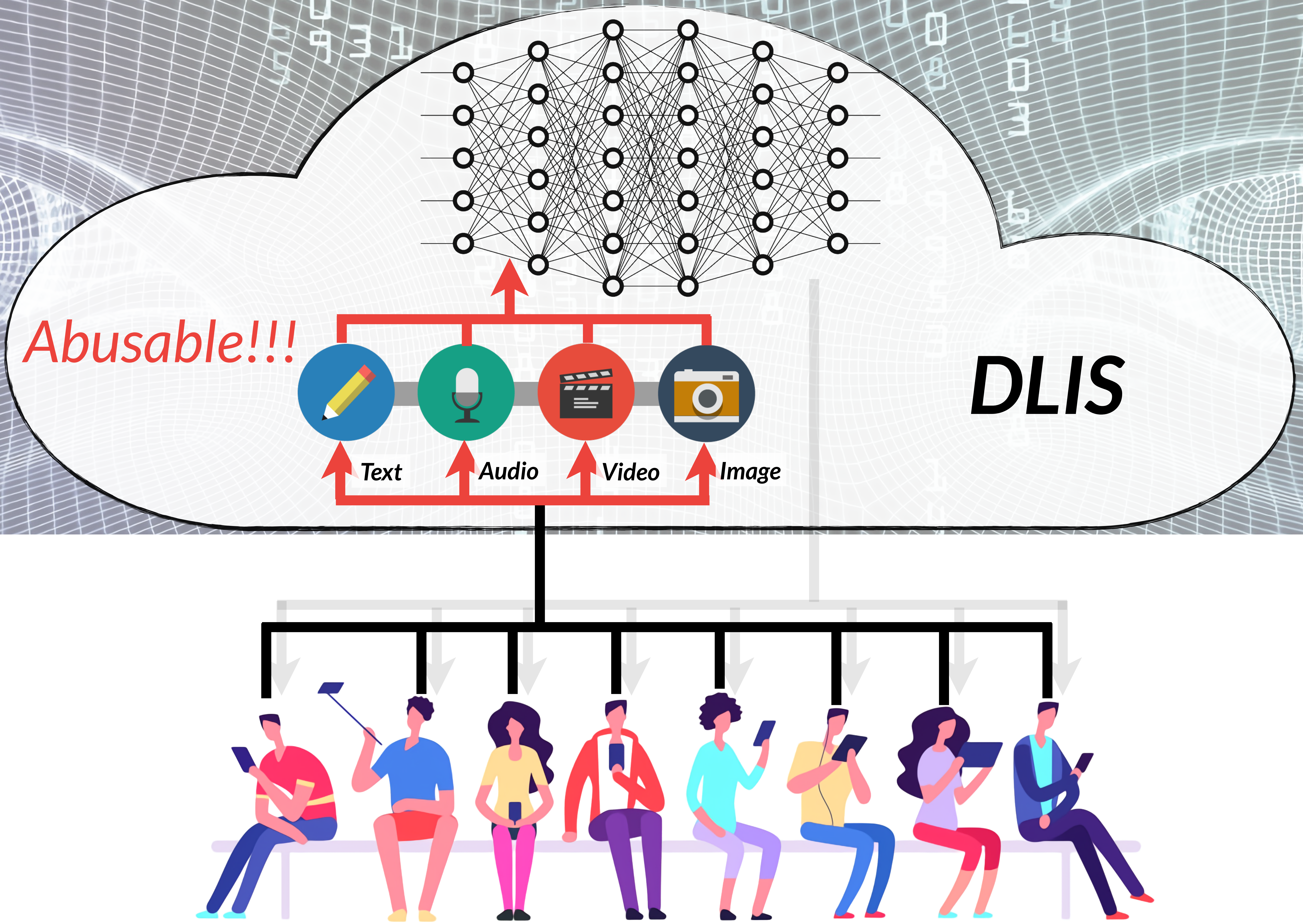

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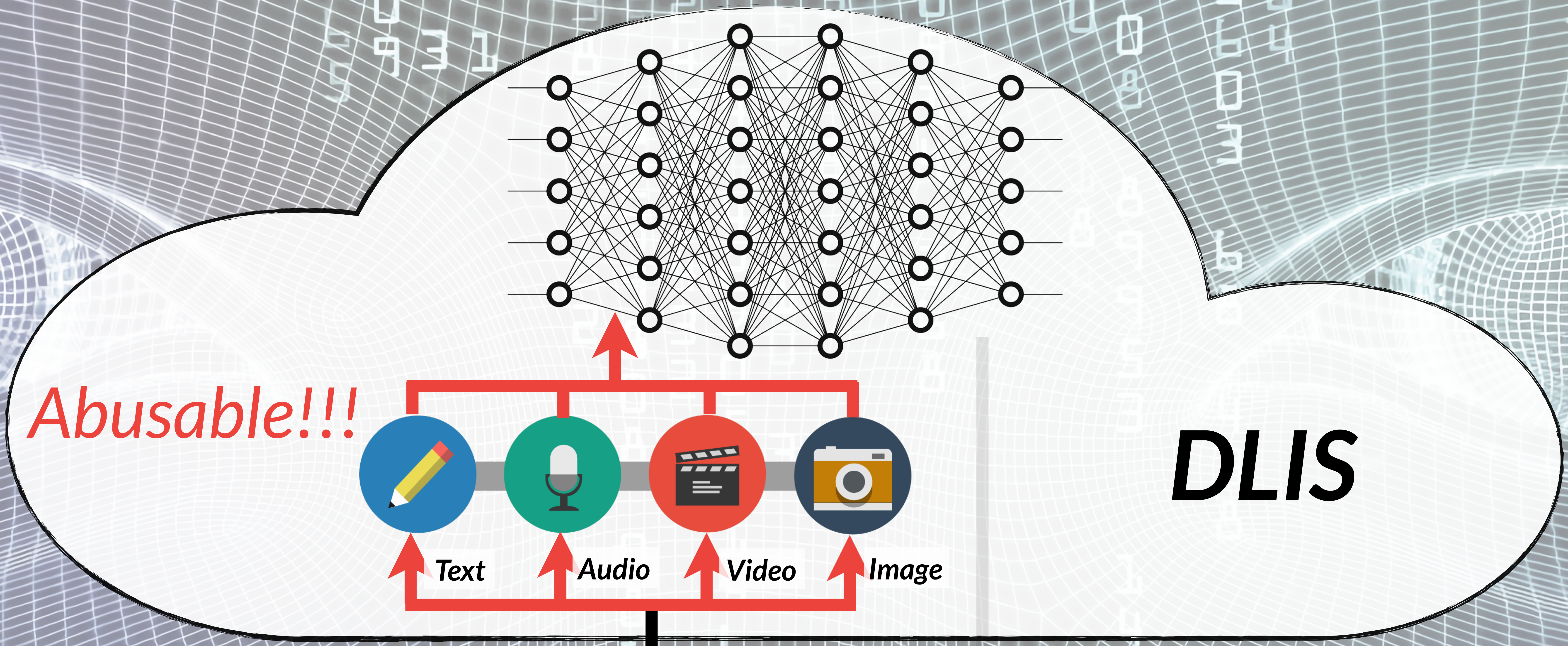
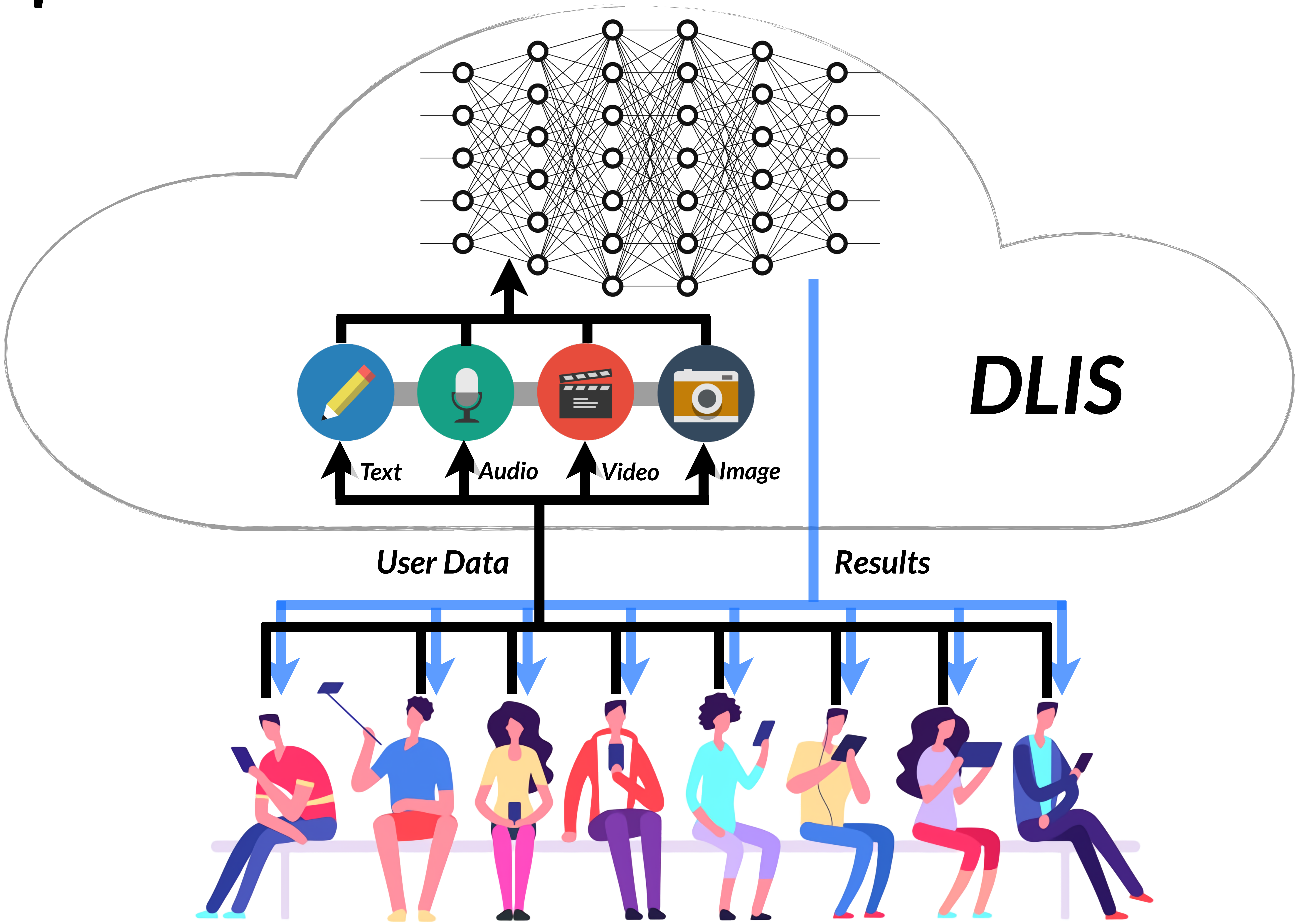



**Data abuse is about the rights of data owners in the context of DLIS.**

1.Infer private info.
2.Train new models.

# Problem Requirements



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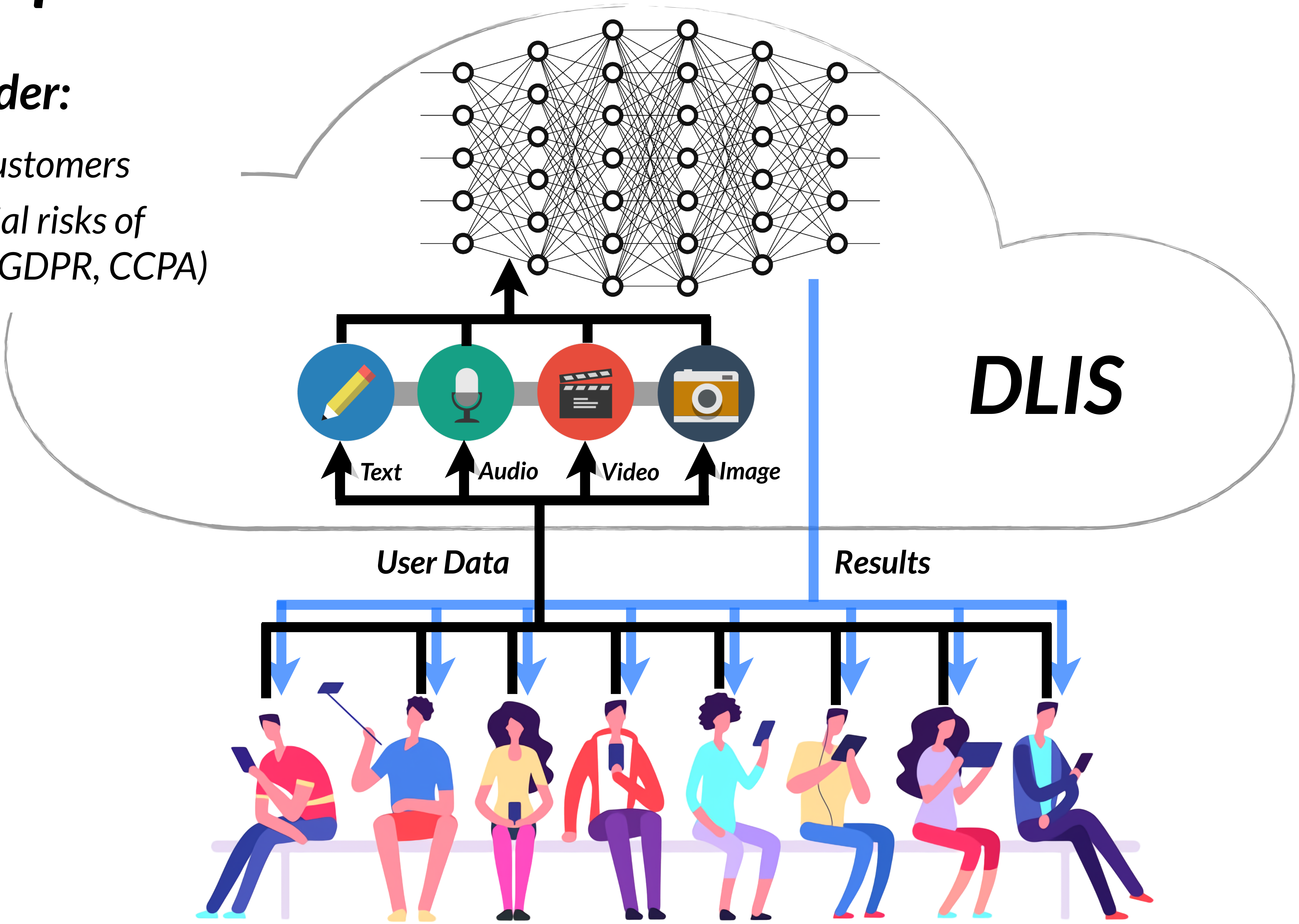
- Attract more customers
- Reduce potential risks of violating laws (GDPR, CCPA)



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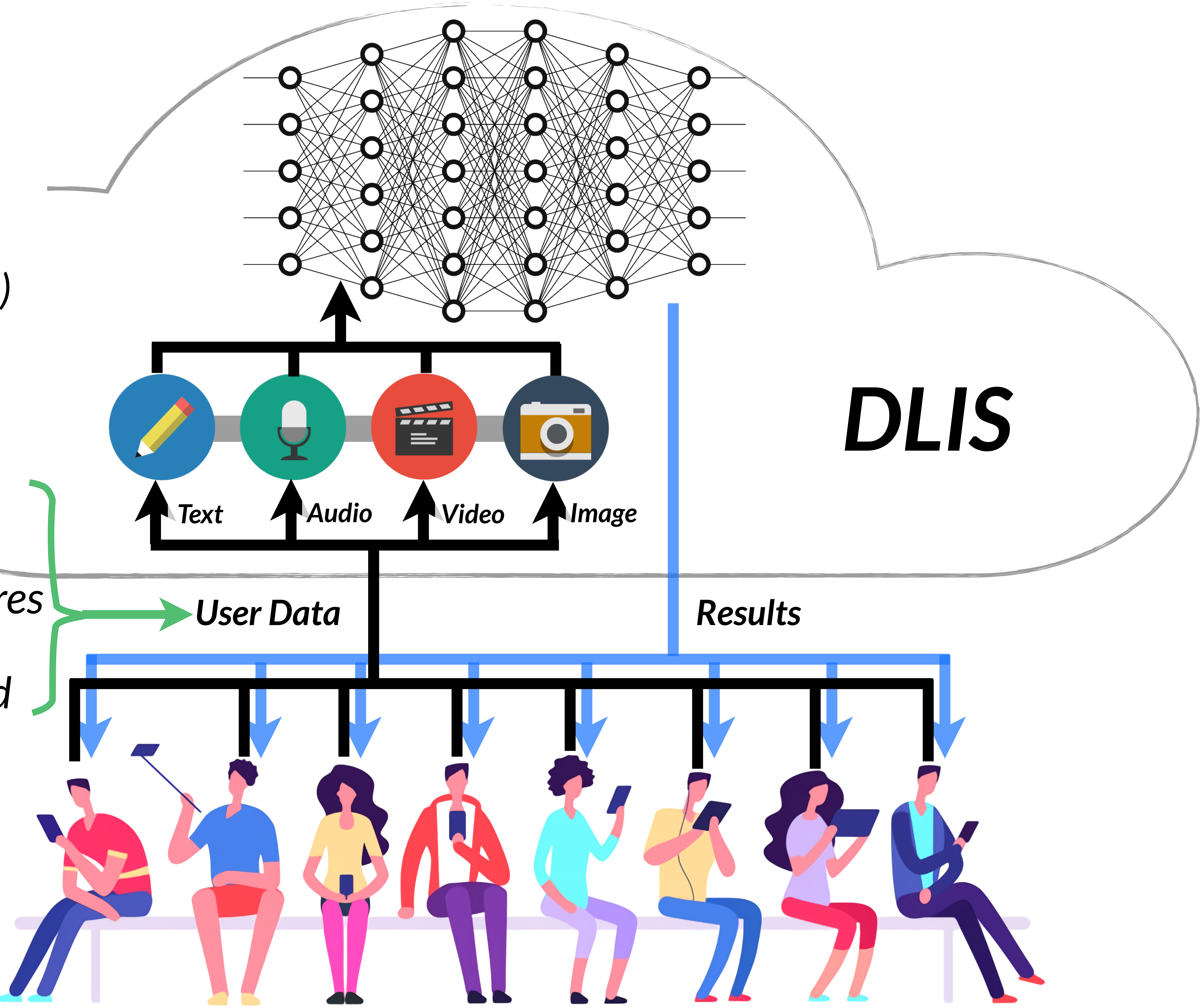

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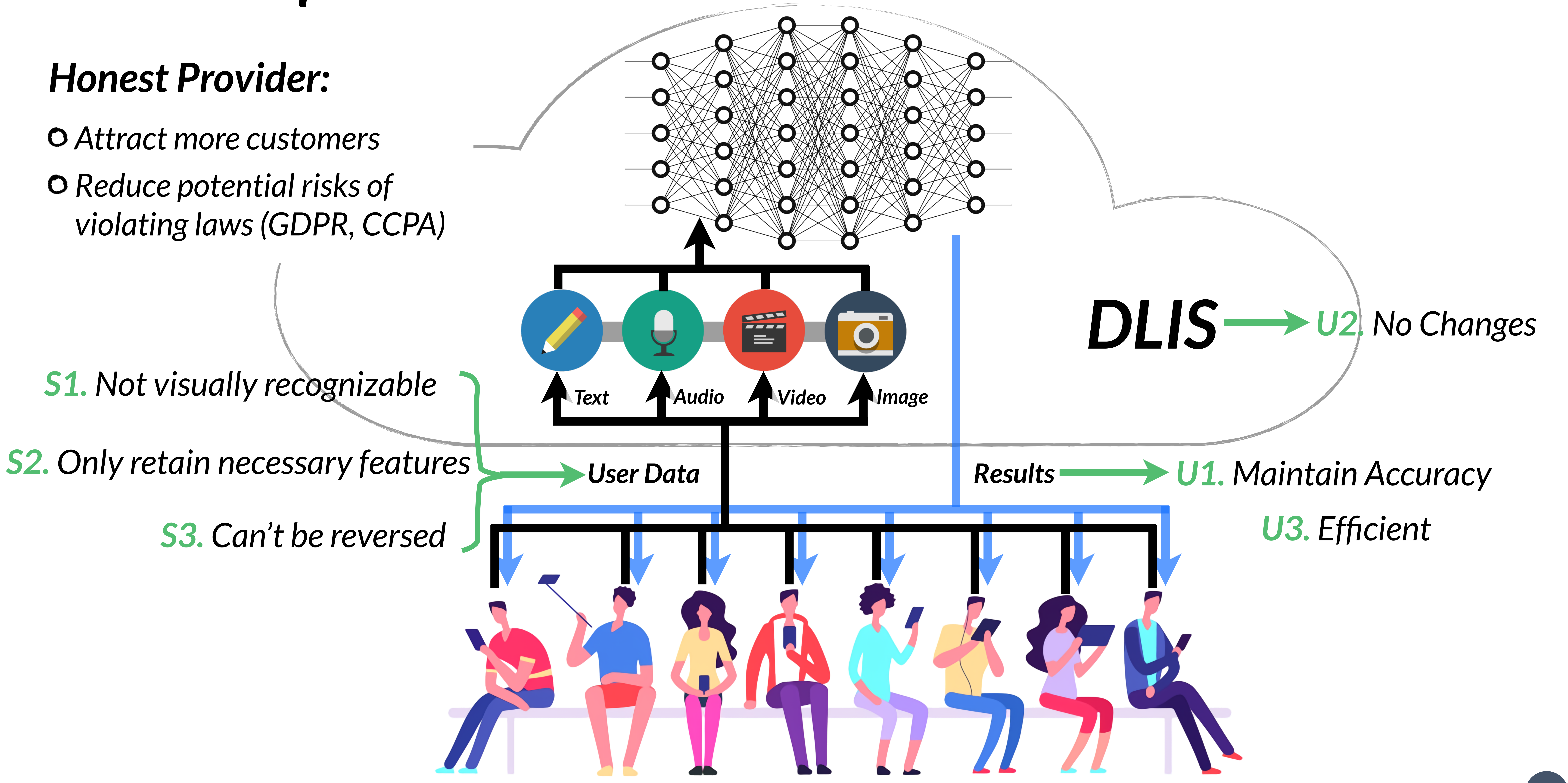

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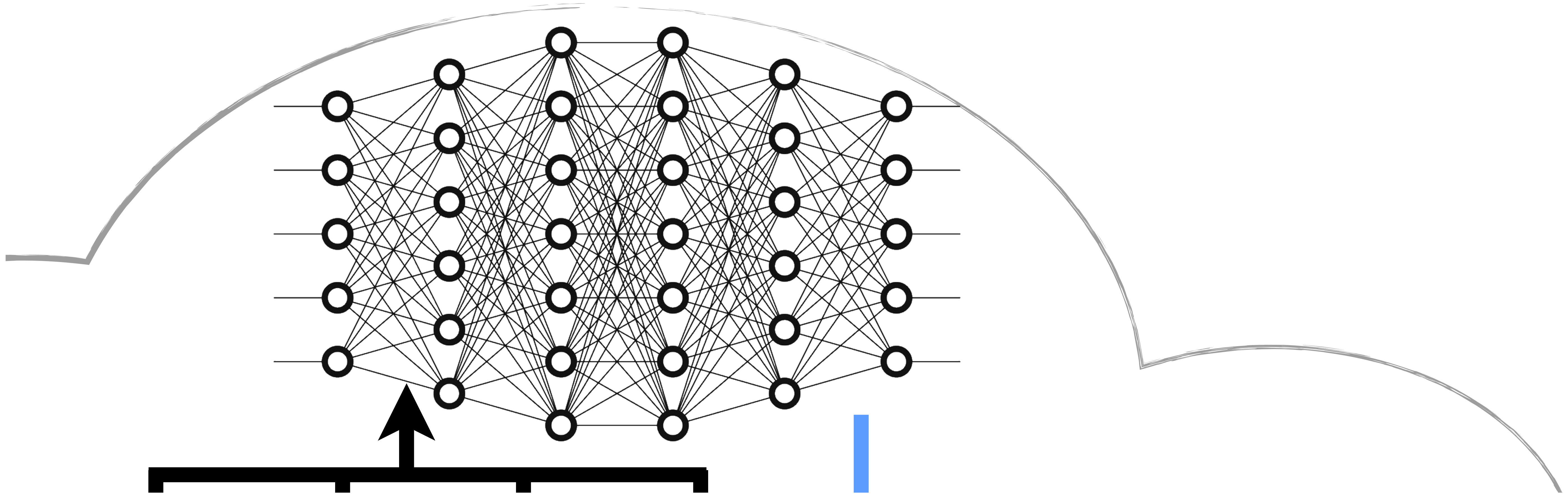

**Honest Provider:**

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- Reduce potential risks of violating laws (GDPR, CCPA)

**Security** ⟷ **Balance** ⟷ **Usability**

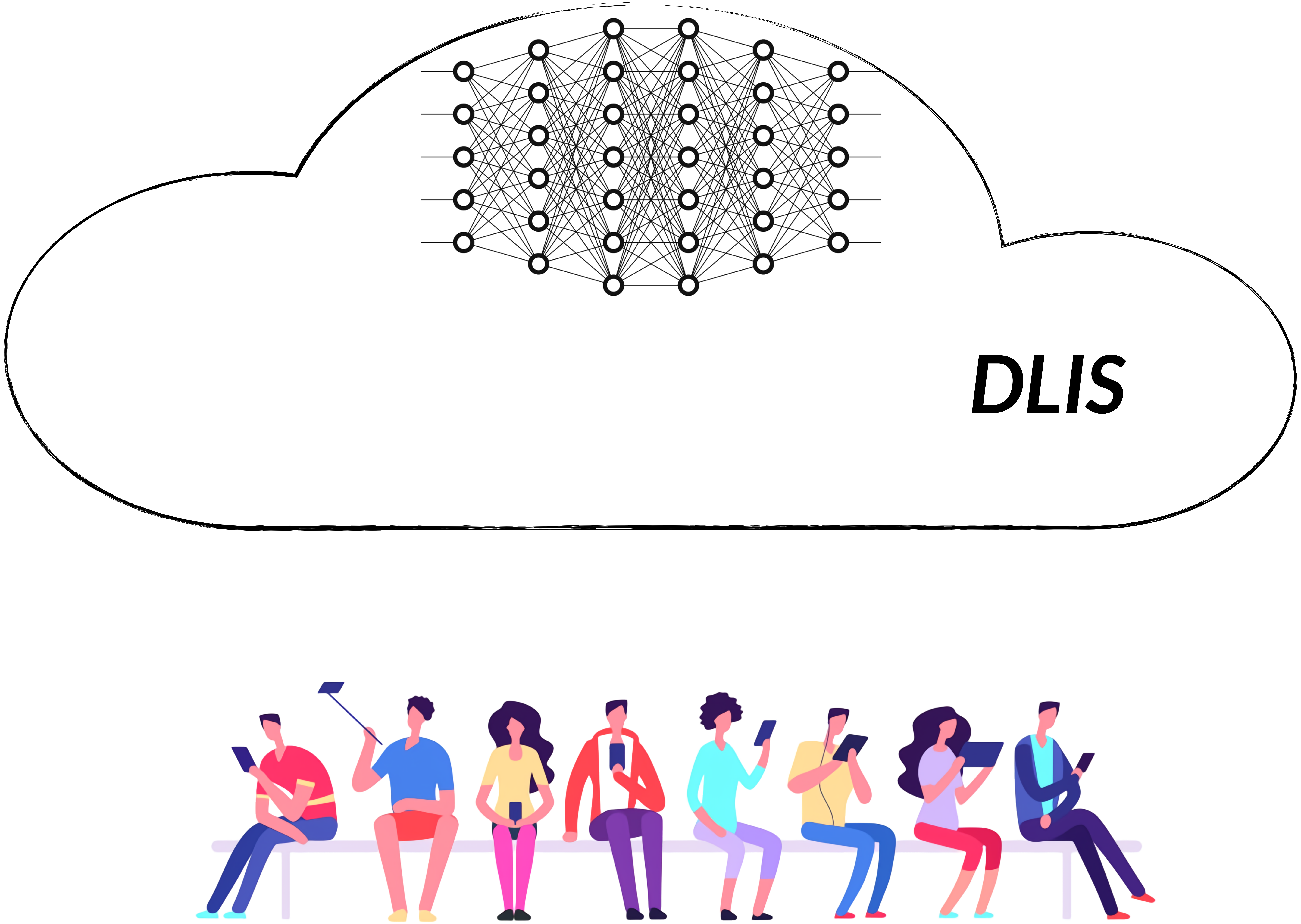
*Weak security solution*

- DP, MP, PAN

*Low usability solution*

- TEE, FHE

# Our solution DAPter



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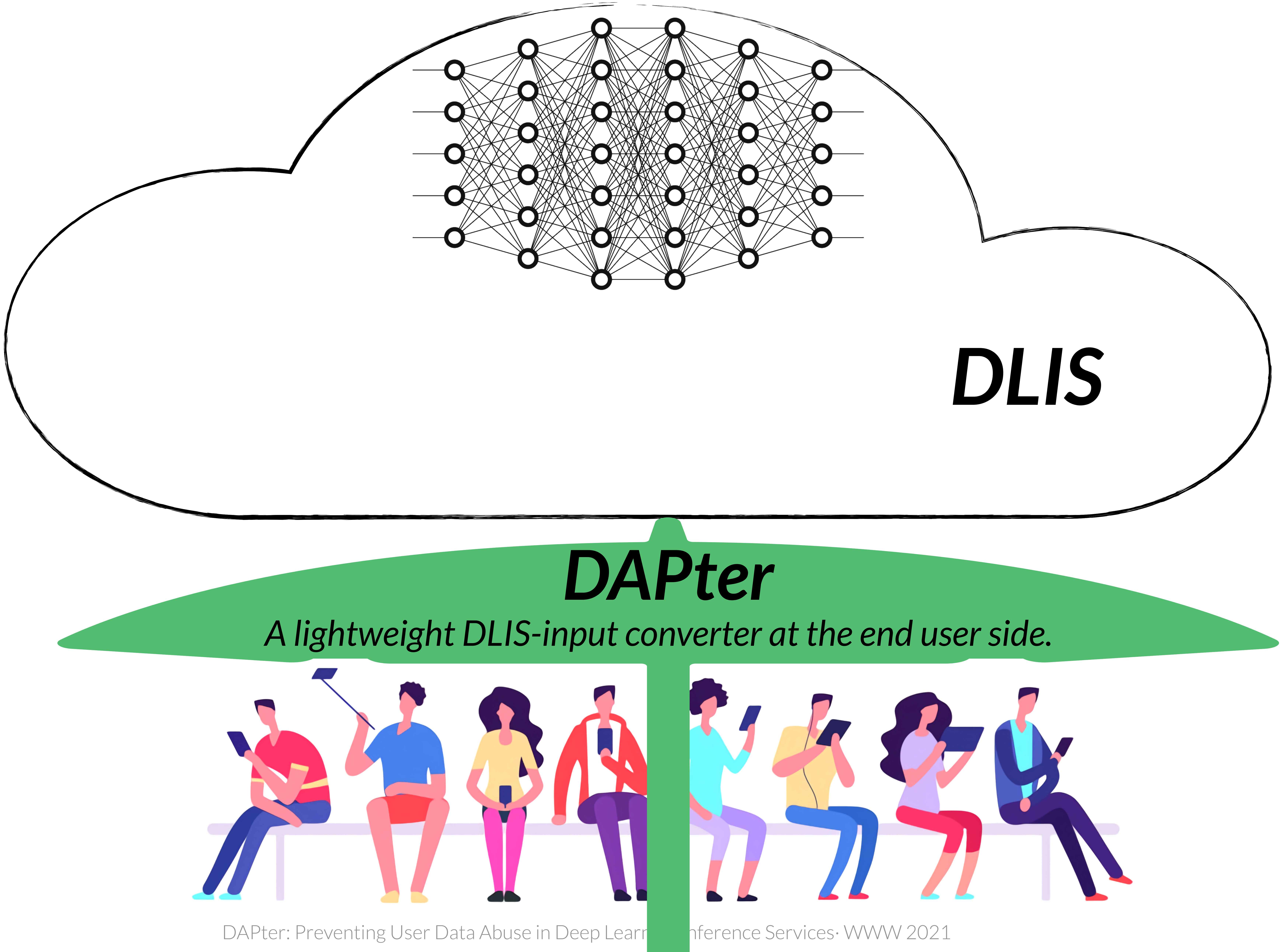

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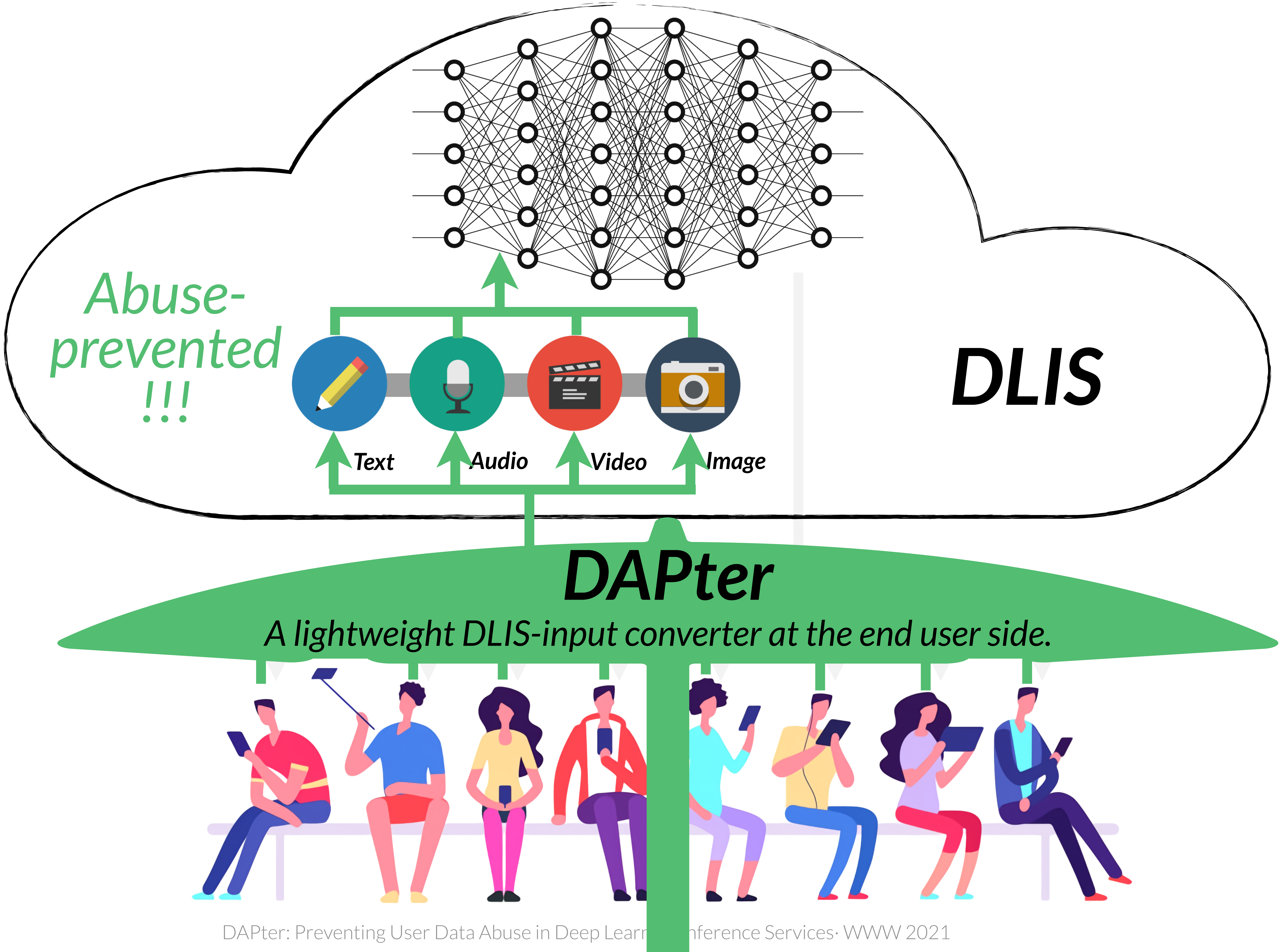
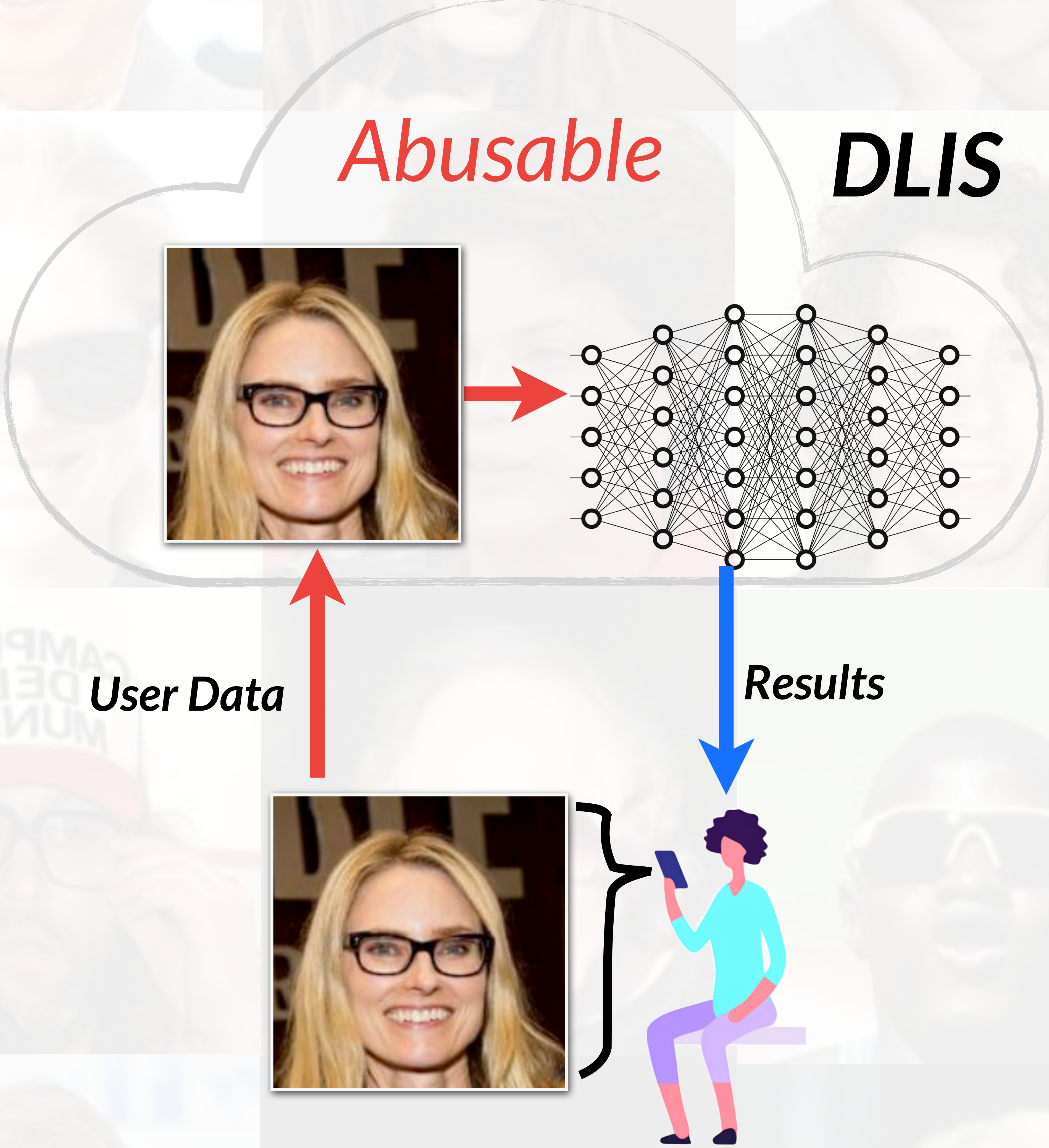
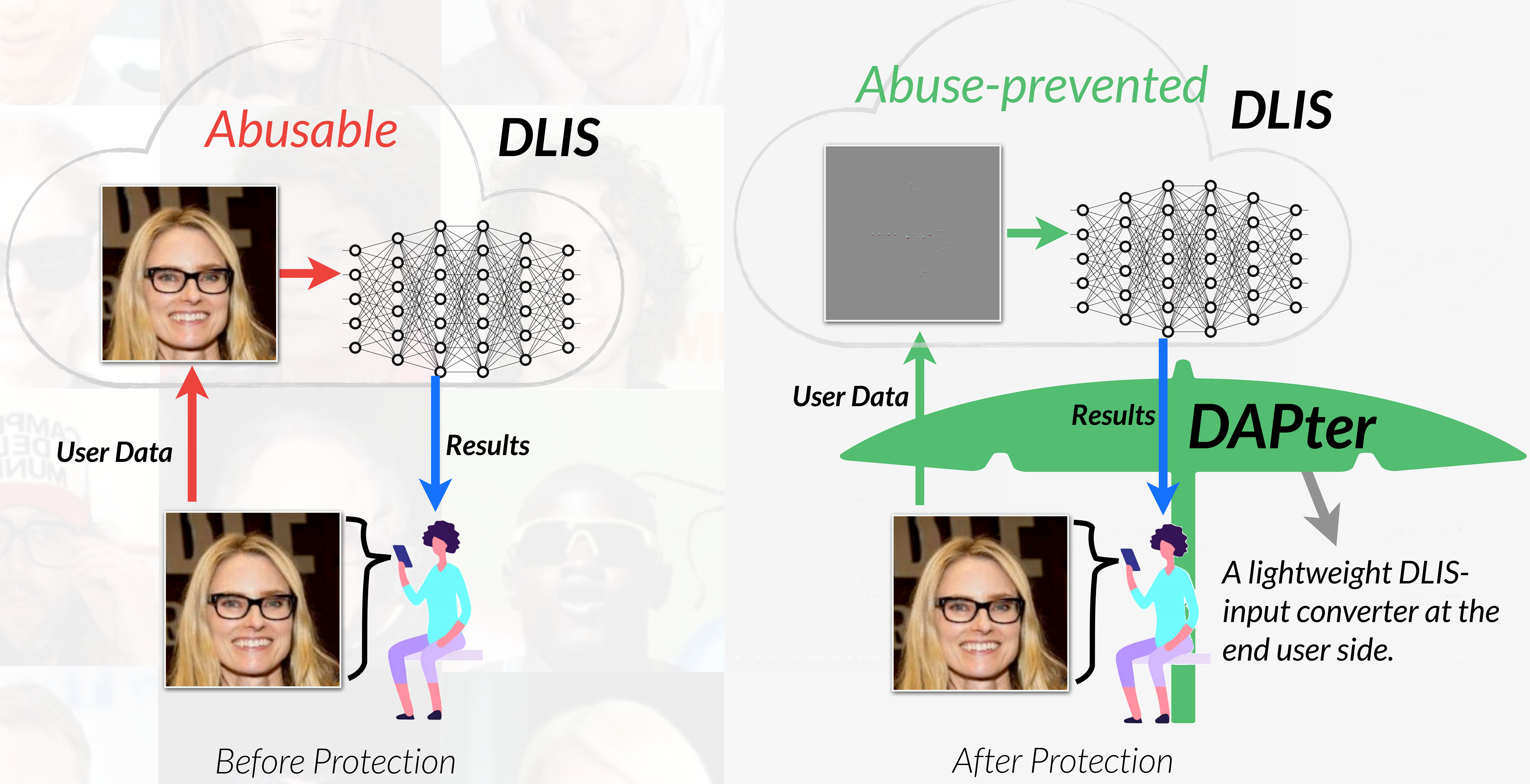


# DAPter Use Case



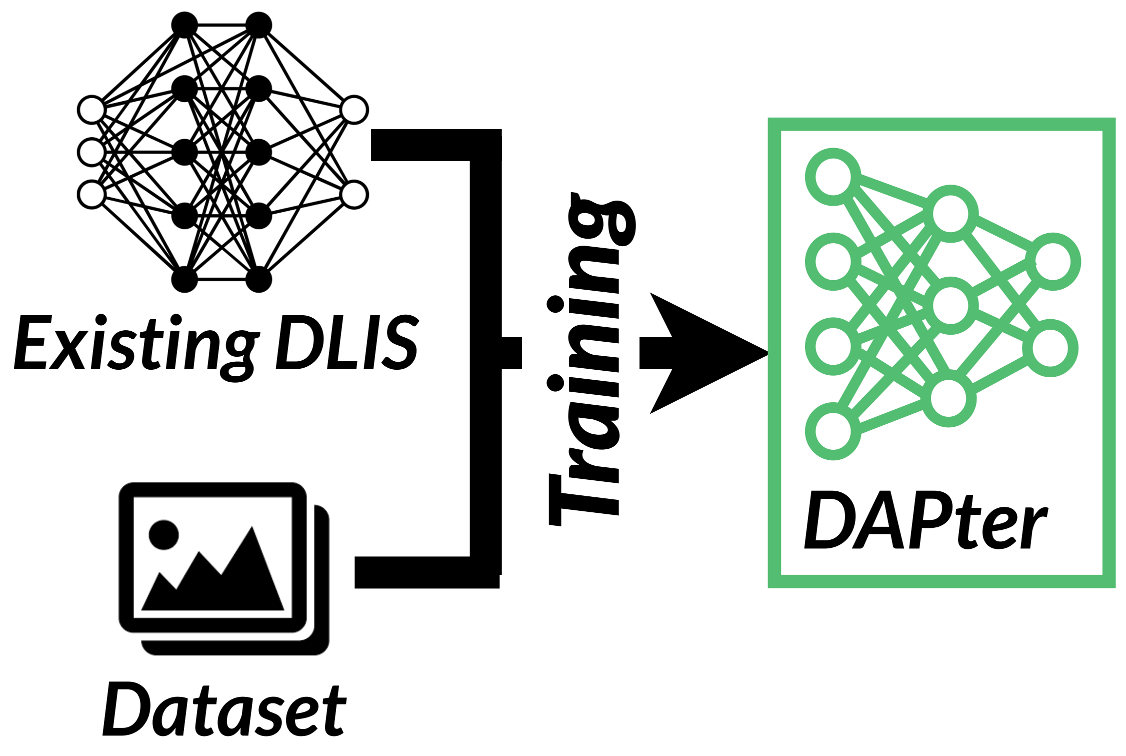

Before Protection

# DAPter Use Case



# Workflow

*A user-side **entropy reduction** approach to **prune information** not relevant to the target DLIS in user data.*



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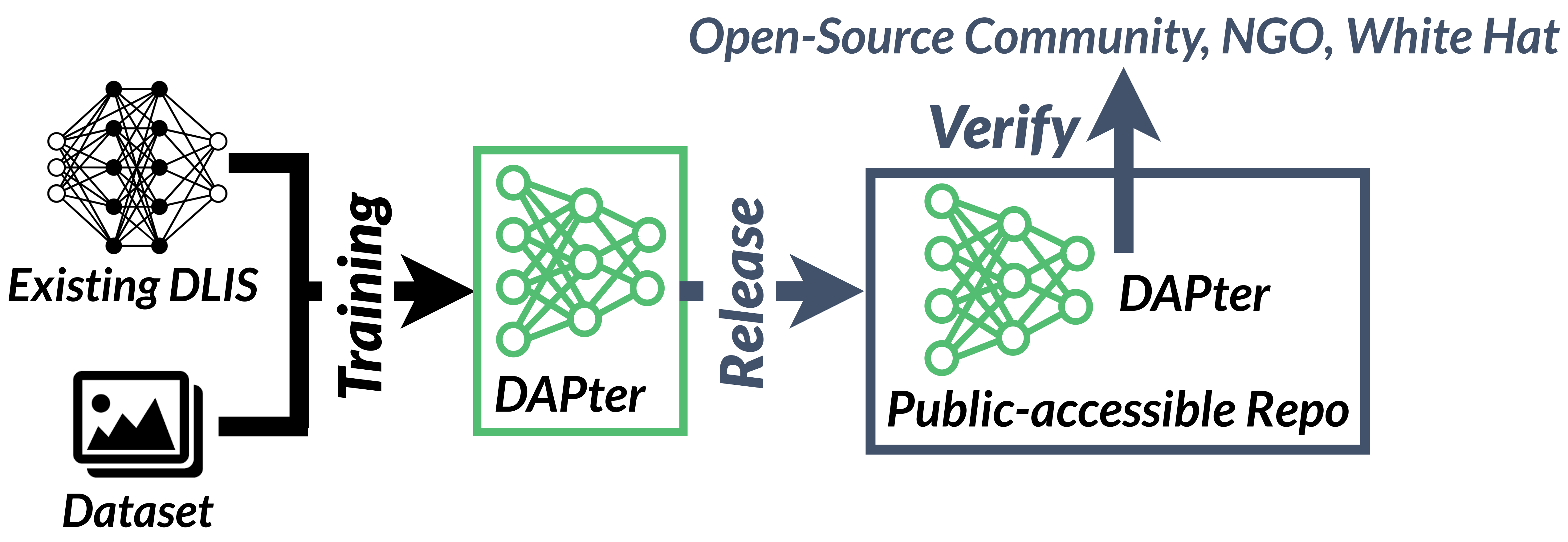

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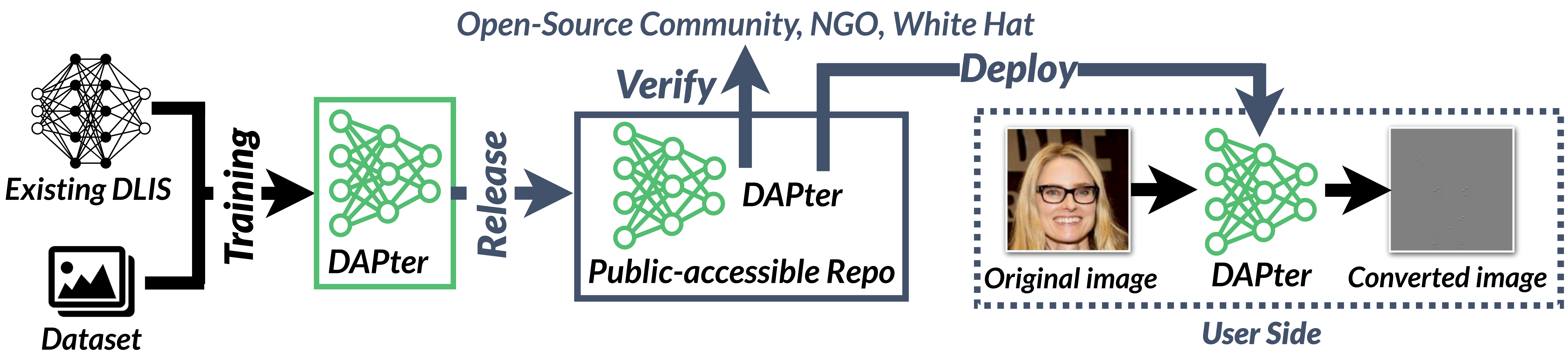

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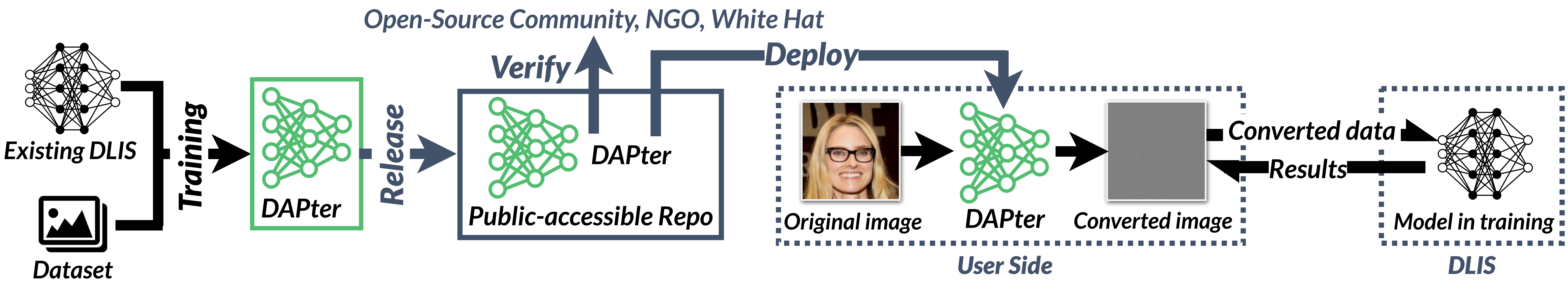

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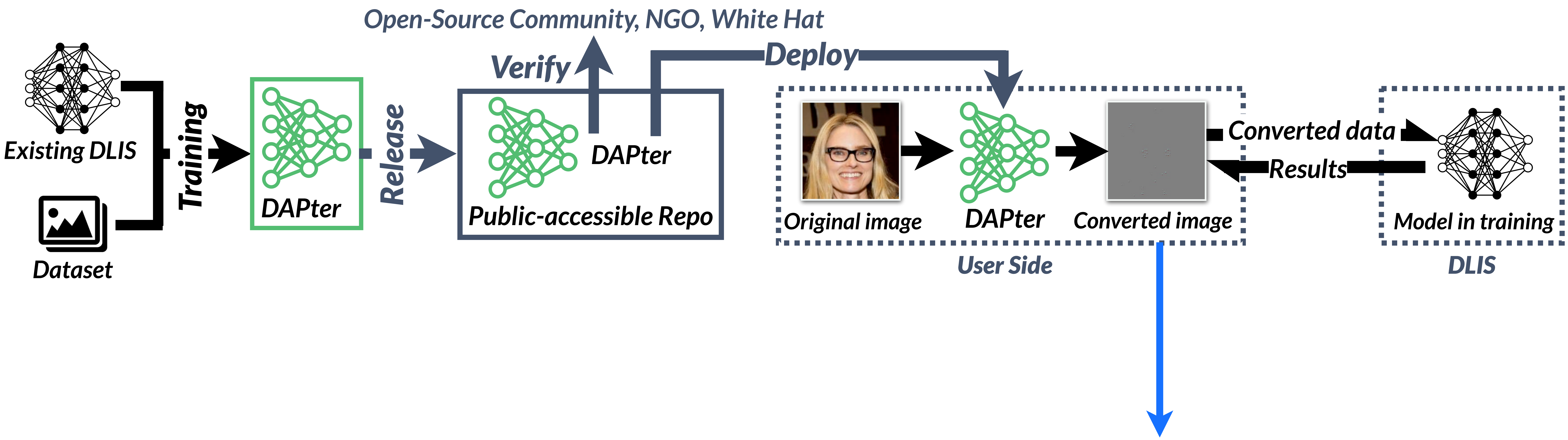


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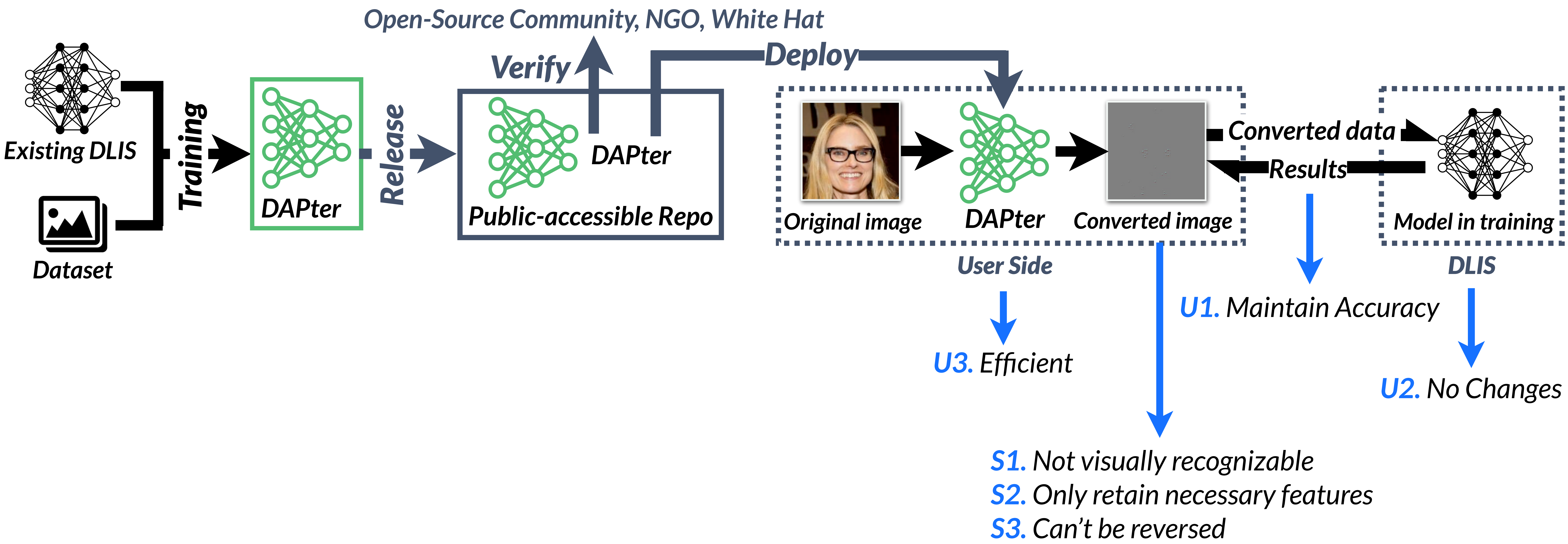

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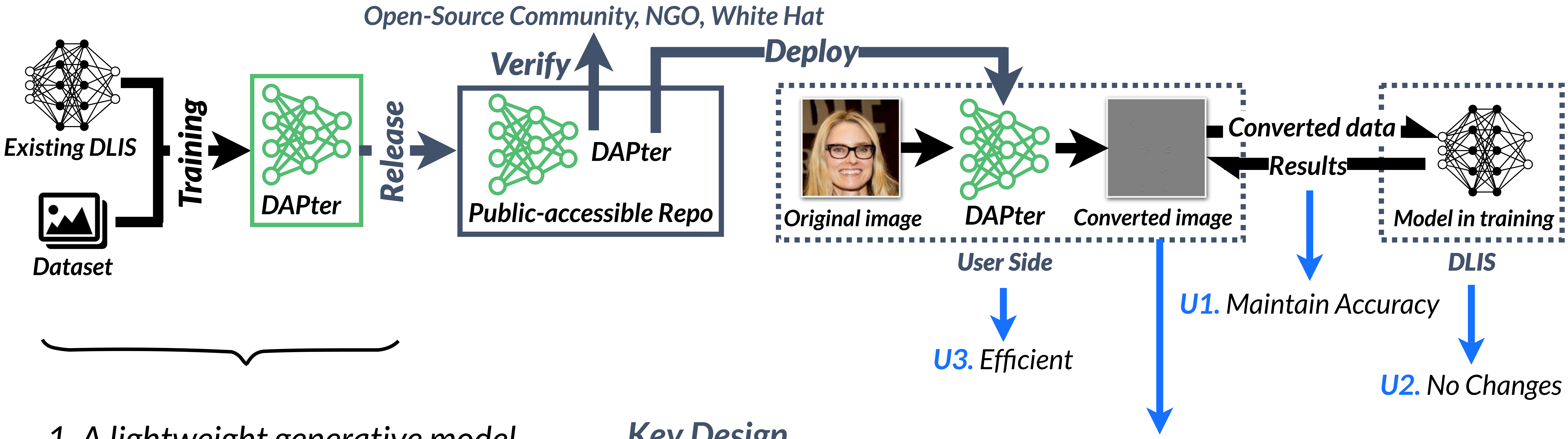


1. *A lightweight generative model*
2. *A data abuse prevention loss*

**Key Design**

*S1. Not visually recognizable*
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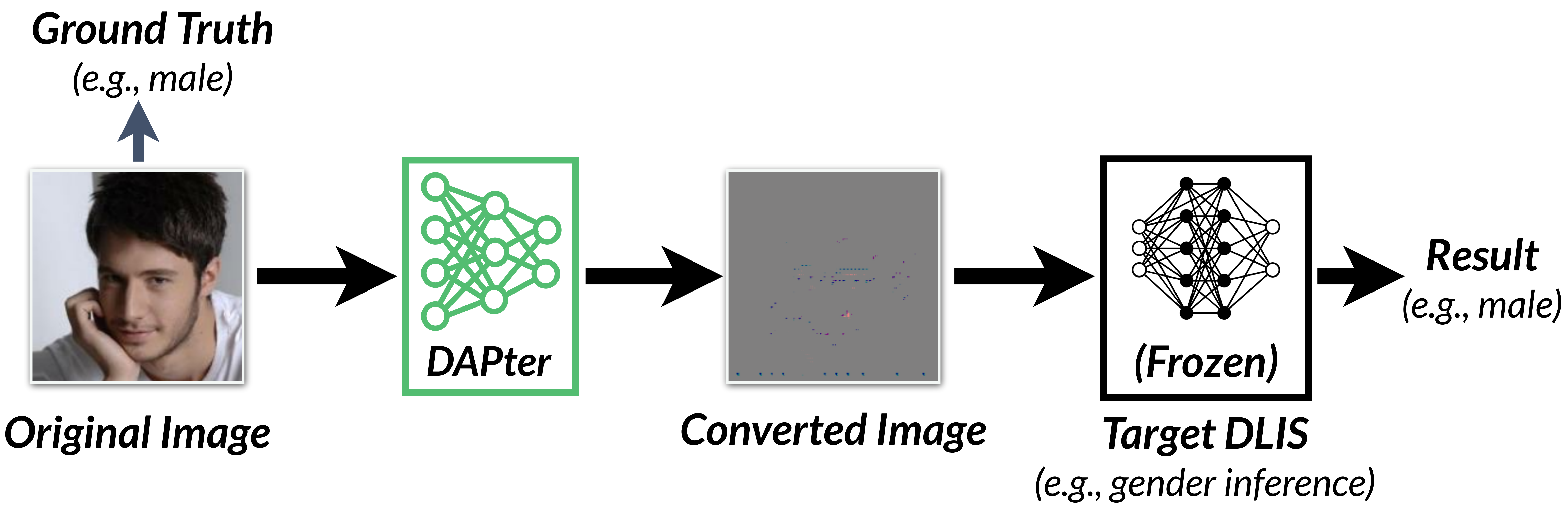
# Training Structure & Model Architecture



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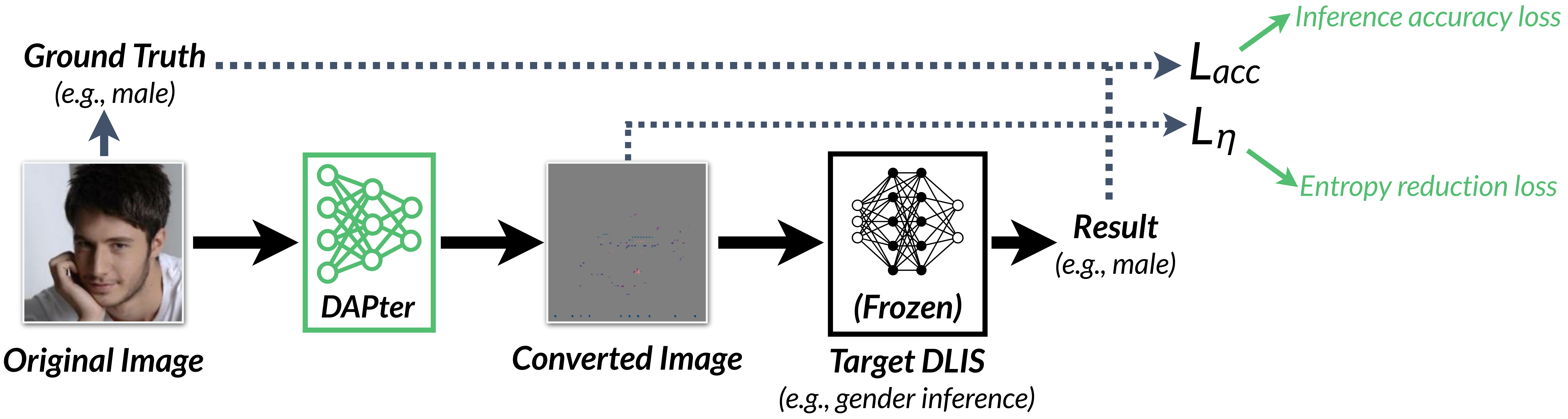

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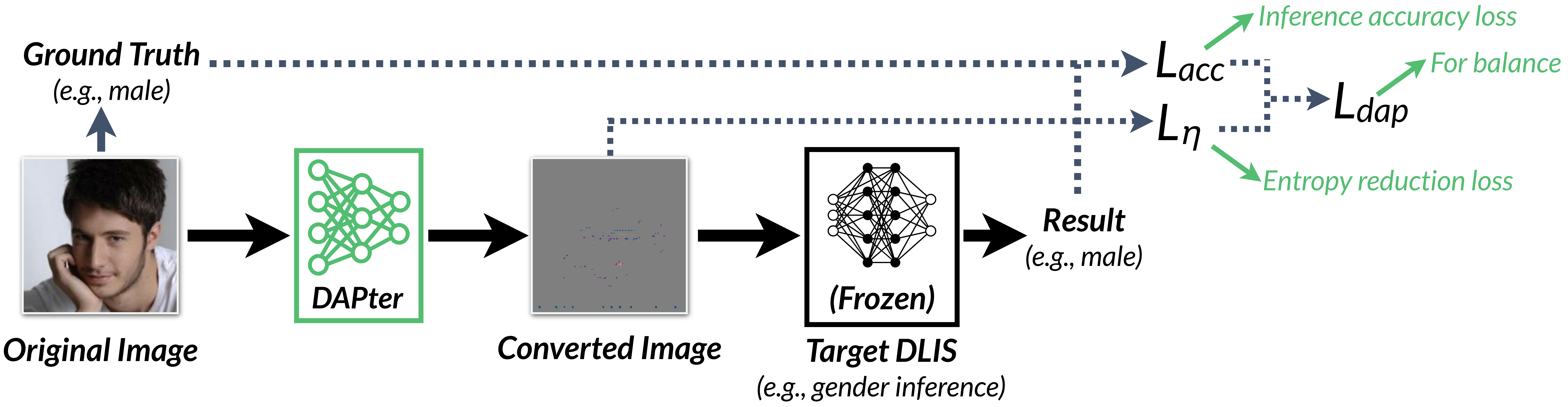

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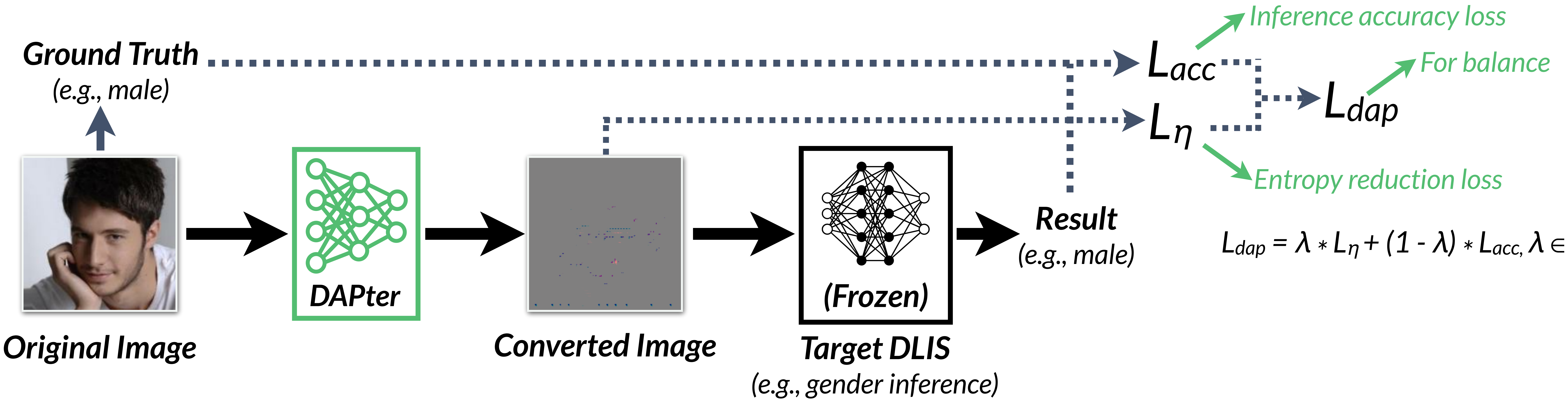


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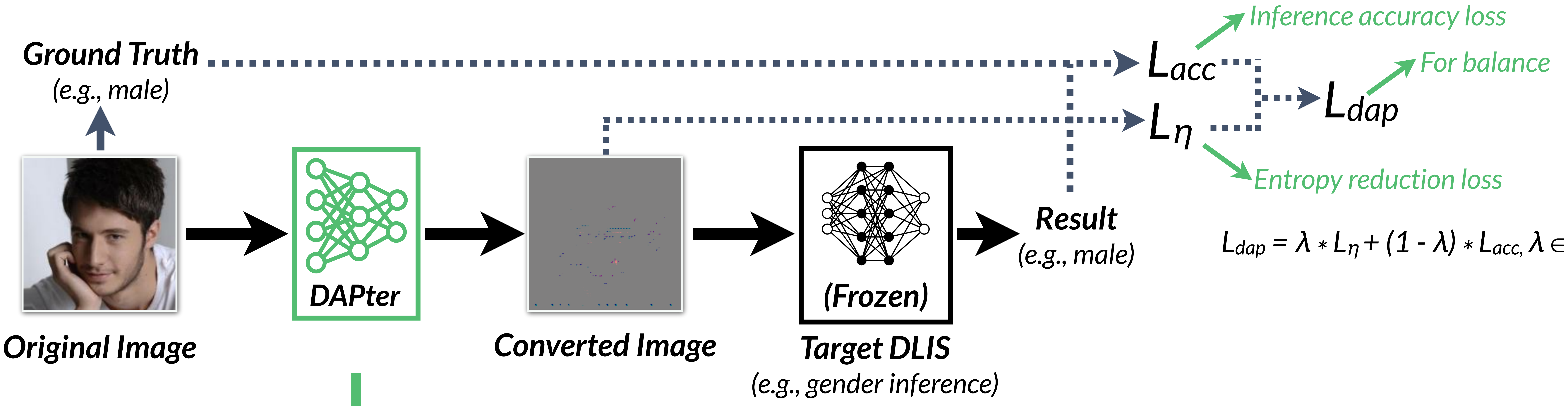


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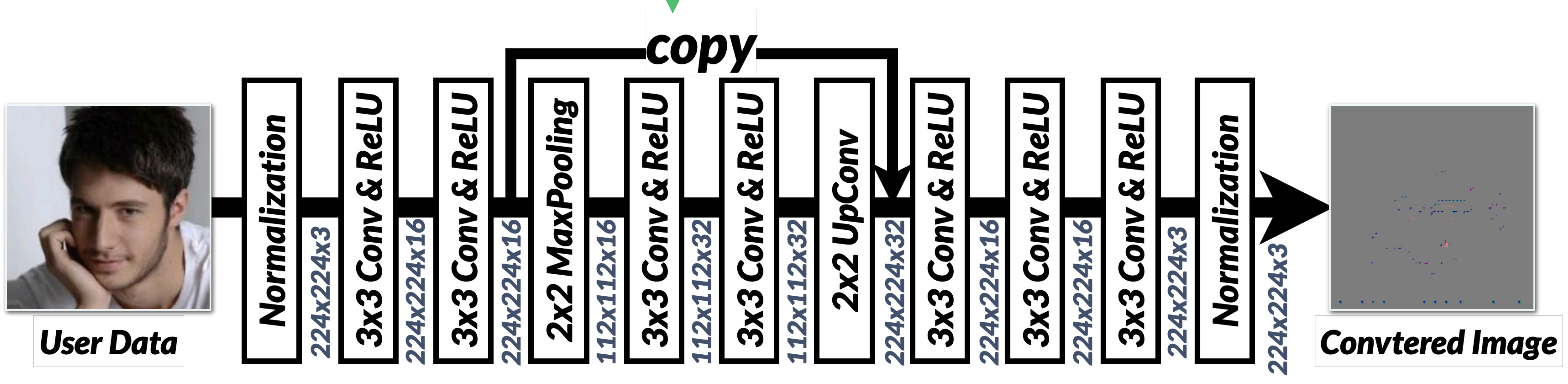


Model Architecture

1. *A symmetrical U-Net like architecture.*
2. *Input and output are of the same size.*
3. *"Copy" connection captures the high-level semantic info and low-level spatial info.*

# *Data Abuse Prevention Loss*

*Minimize the piece of pixel-wise entroy that contributes little to the high-level features.*

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$$L_{\eta} = \sum_I \eta(I, I_{ref})$$

***η*** *is L1 norm;* ***I*** *is the converted image;* $\mathbf{I_{ref}}$ *is the reference image with each pixel equaling to (R128, G128, B128).*

**Proof can be found in our paper*

# Heyperparameter λ Exploration

$$L_{dap} = \lambda * L_{\eta} + (1 - \lambda) * L_{acc},\ \lambda \in (0, 1)$$

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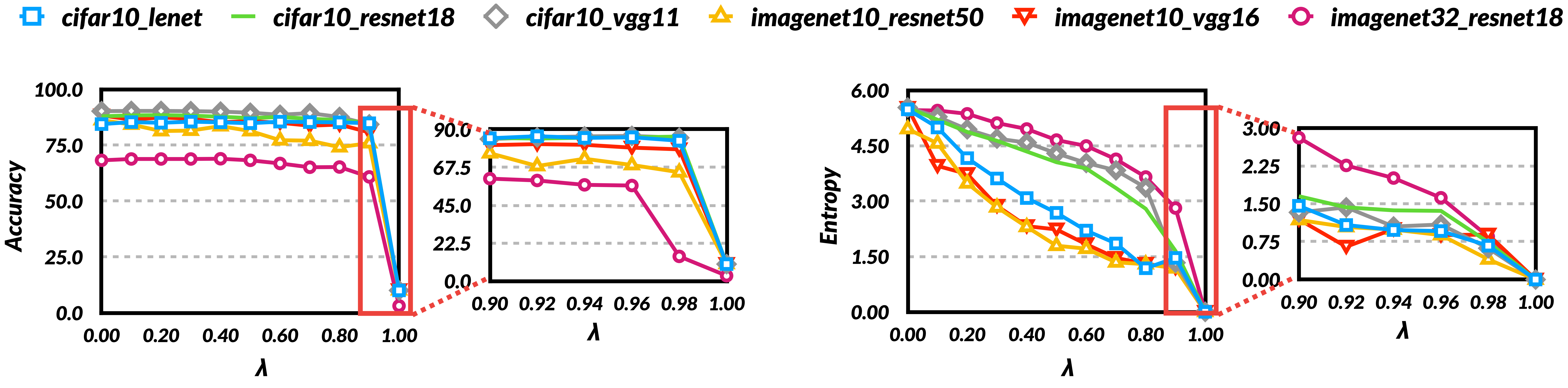


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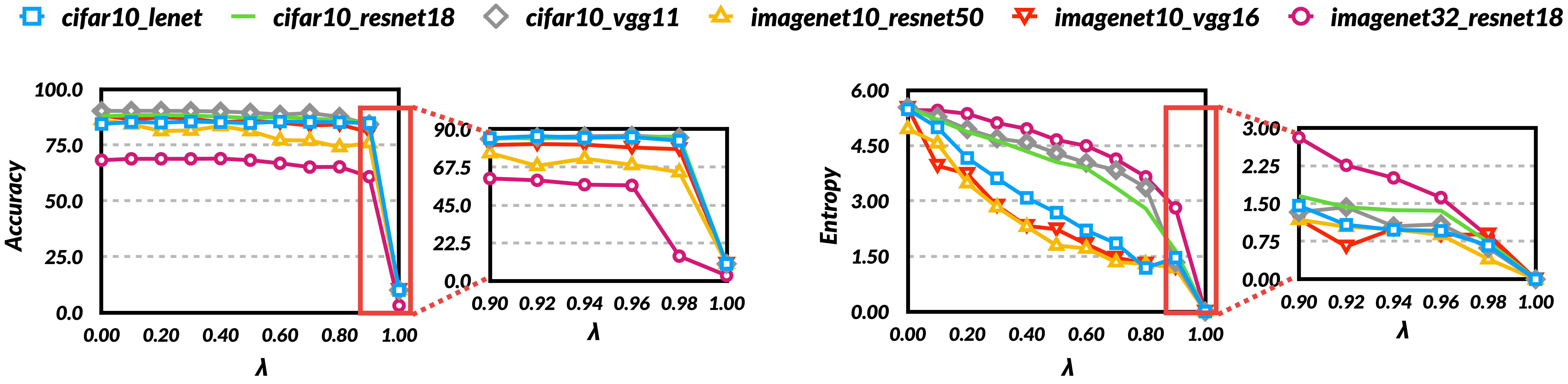


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***(b) Relationship between λ and Entropy***

*λ = 0.9 is a sweet point to balance security and usability.*

# Conversion Quality

*To show that DAPter can remove the unnecessary features and retain the useful features, we generate saliency map (SM) to measure which part of the input supports the DLIS through Grad-CAM.*

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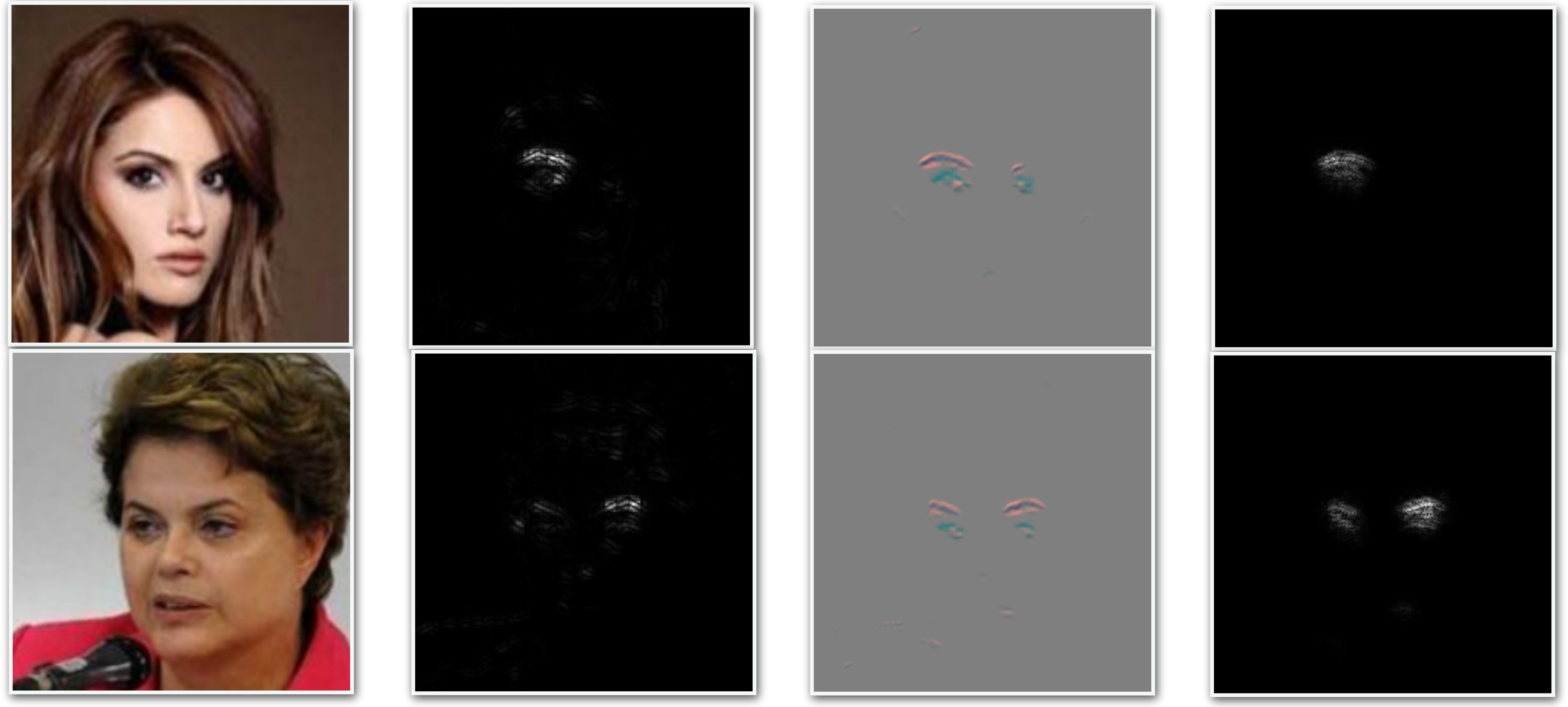
*Results are visualize below. From left to right is original image, sm of DLIS, protected image, sm of DAPter-enabled DLIS.*



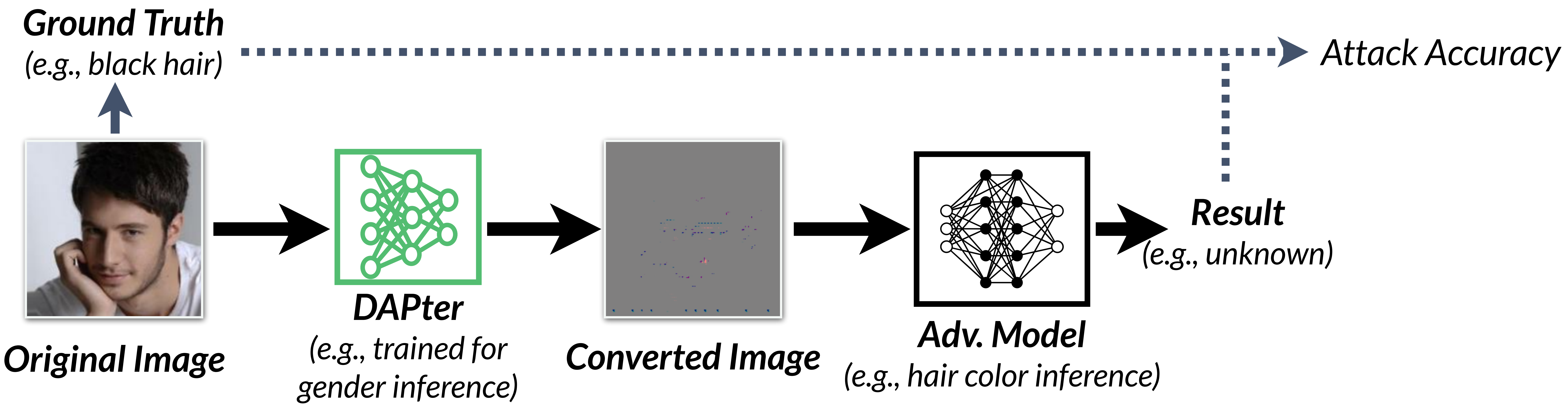
*(a) Arched Eyebrow Inference*

*(b) Wearing Glasses Inference*

*(c) Gender Inference*

# *Security - Auto Recognition Attack*

*The adversary can use SOTA DL model to label the entropy-reduced outputs of DAPter.*



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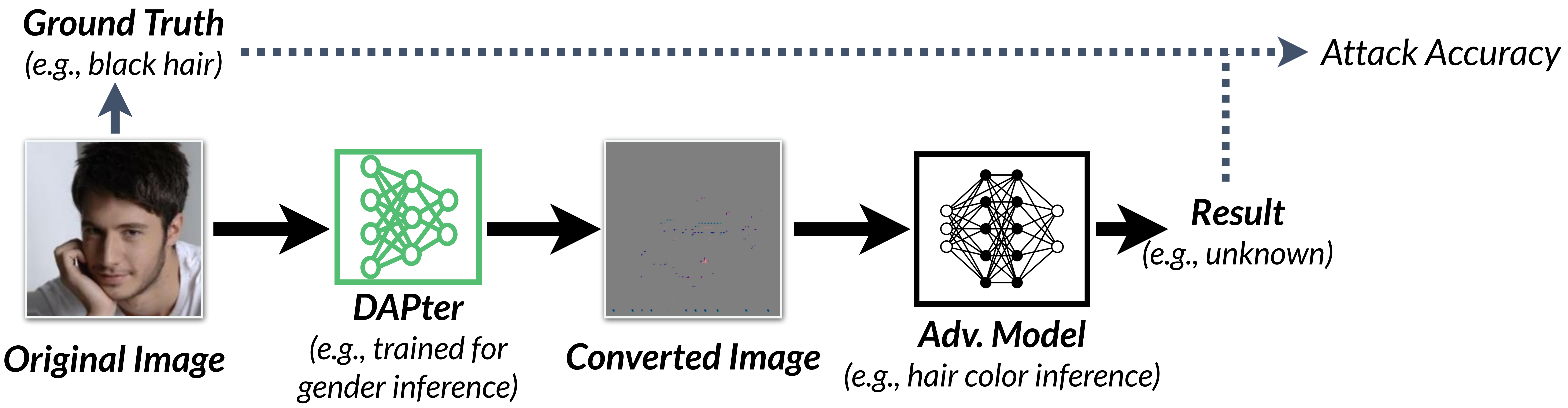
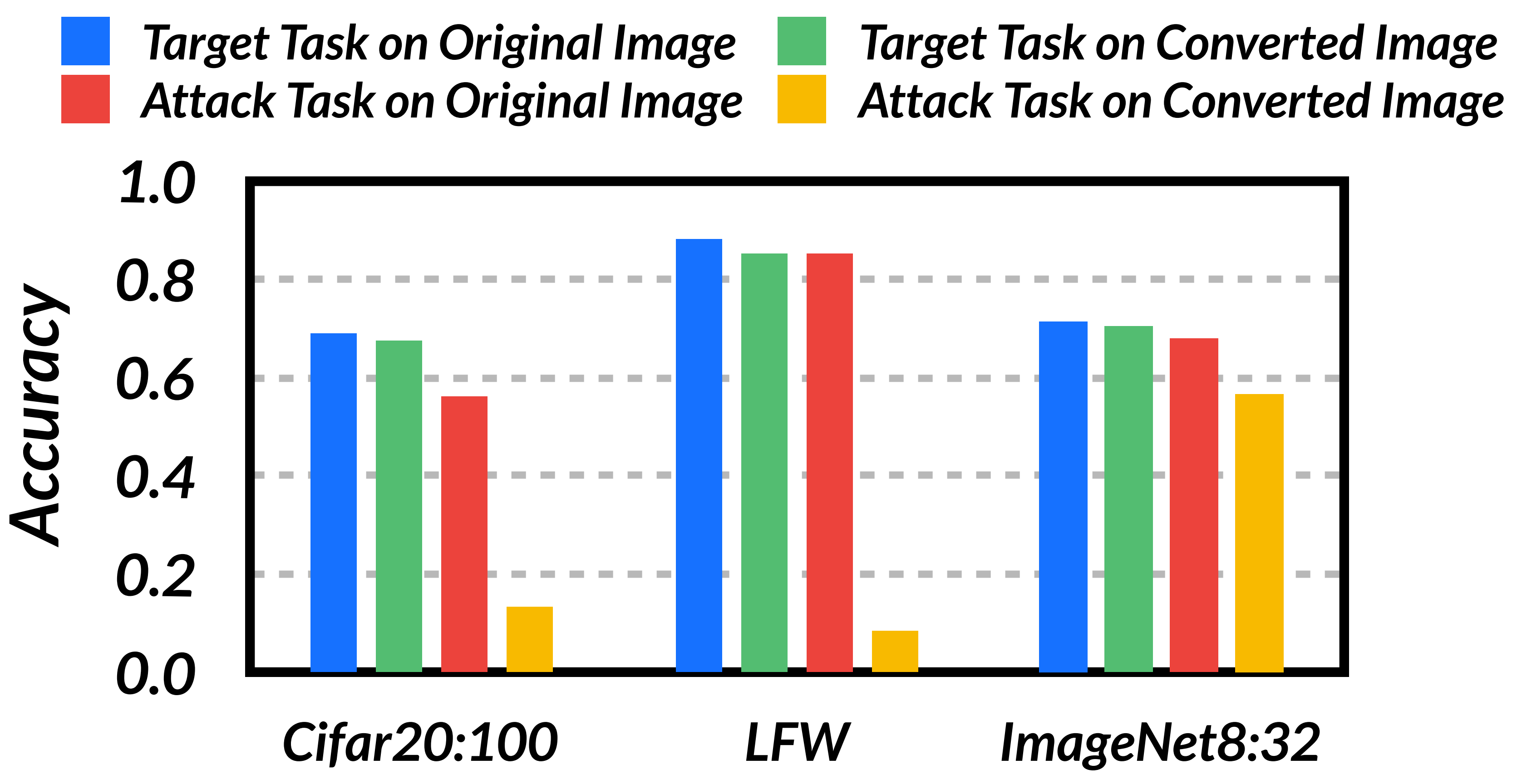
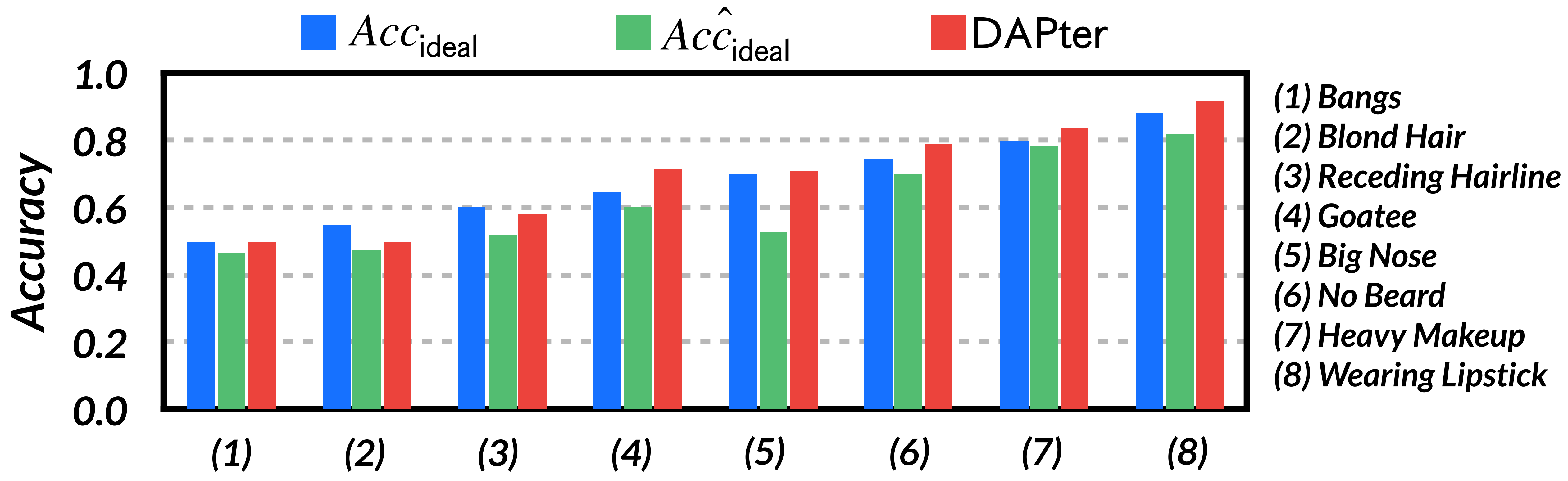


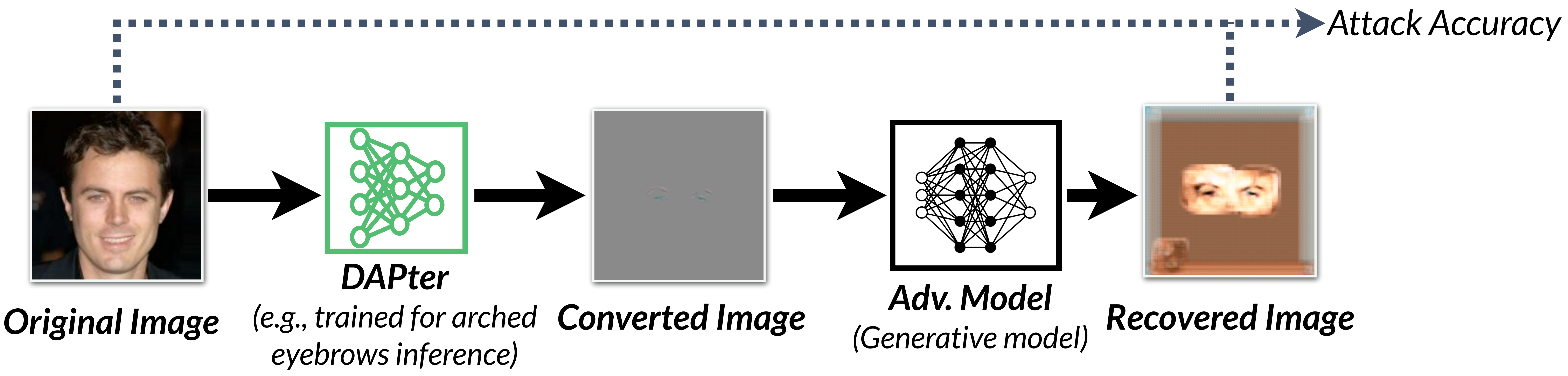

***Case 1:*** *Attack tasks have no correlation with the targeted task.*




***Case 2:*** *Attack tasks have correlations with the targeted task.*

# Security - *Image Reconstruction Attack*

*The adversary can use SOTA DL model to reconstruct the origianl image from the protected one.*



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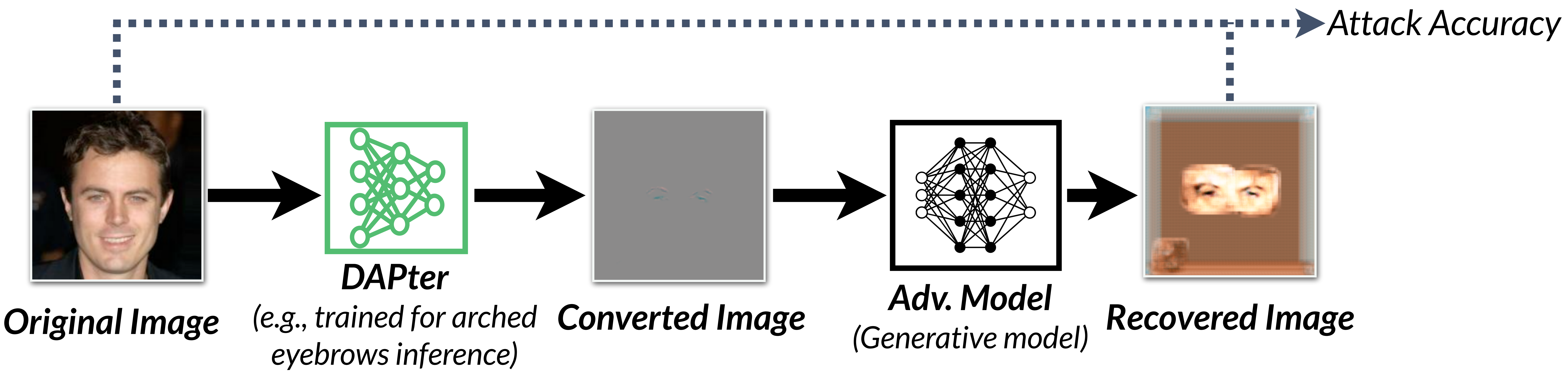
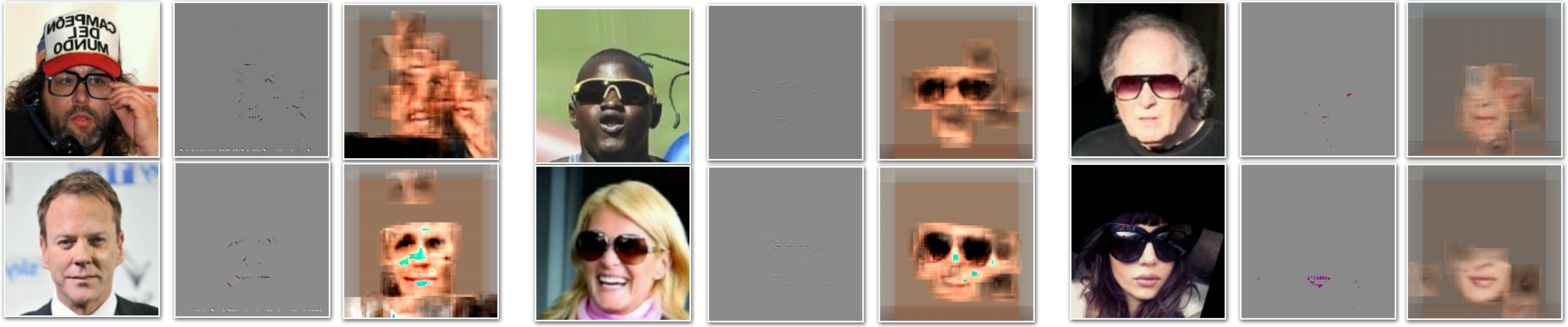
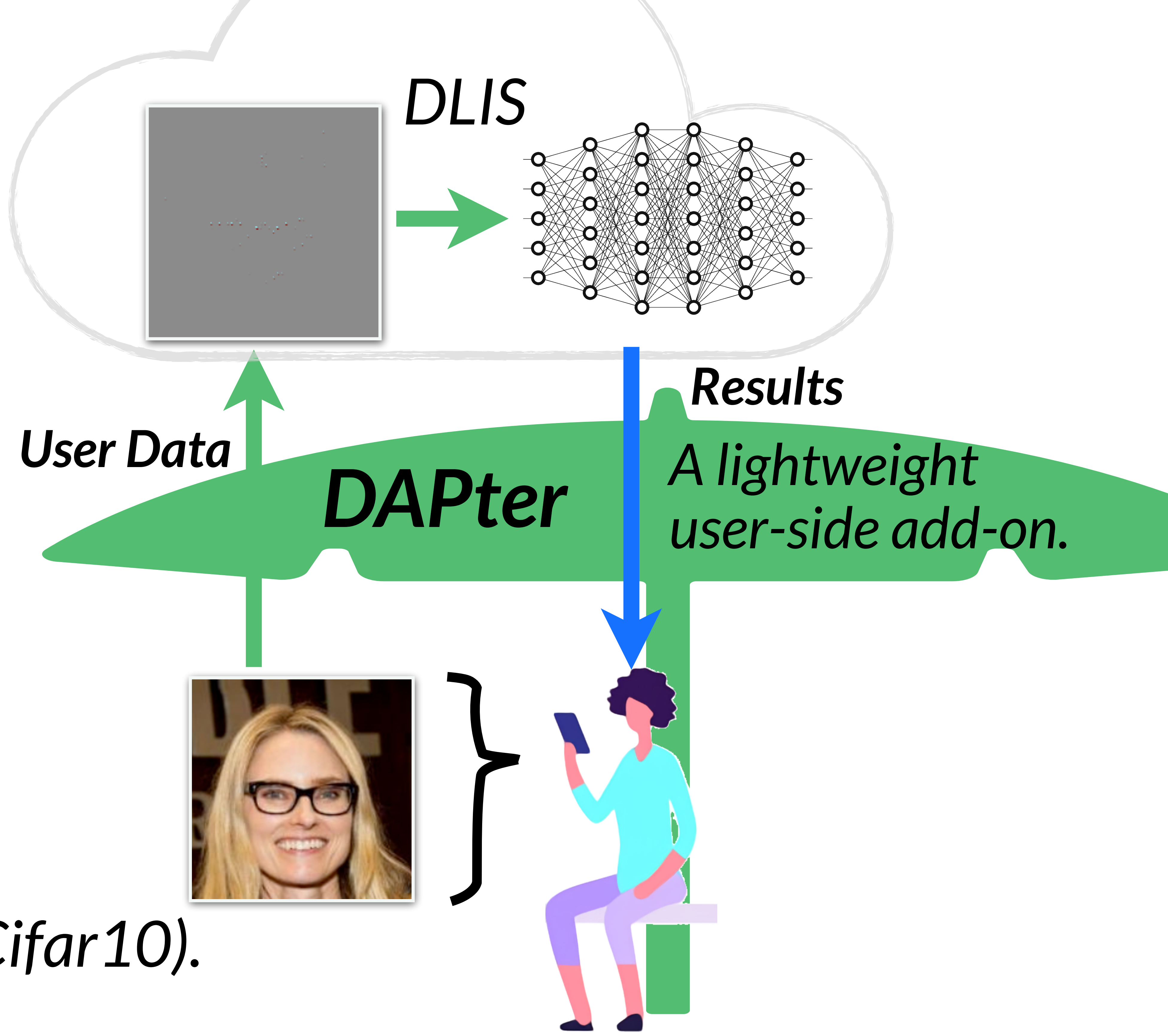


*(a) Chubby Inference Task* *(b) Wearing Glasses Inference Task* *(c) Wearing Lipstick Inference Task*

# *Usability Evaluatuion*




## Backend Throughput:

- *Compare to TEE-based solution:* ***2.5x~50x**,*
- *Compare to FHE-based solution:* ***1000x**.*

## Bandwidth Usage:

- ***2.1x~41x** better (measured with LFW, ImageNet, CelebA, Cifar10).*

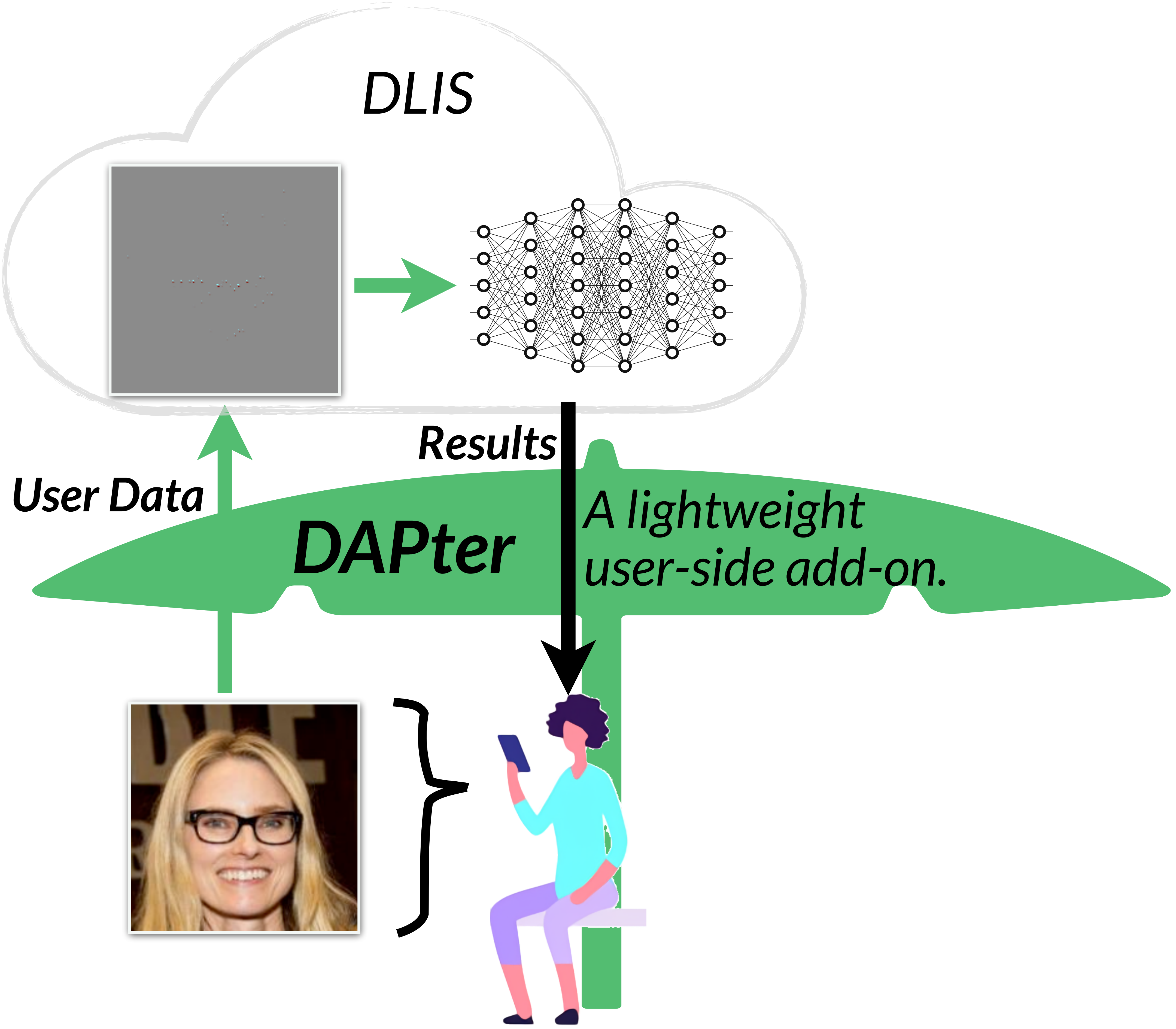
## Latency Overhead:

- ***109ms** (Snapdragon 855 Plus), **292ms** (Kirin 960), and **309ms** (Helio X30).*

***No DLIS backend change is needed!!!***

# Take away

*First investigate the data abuse issue in the scenario of DLIS.*



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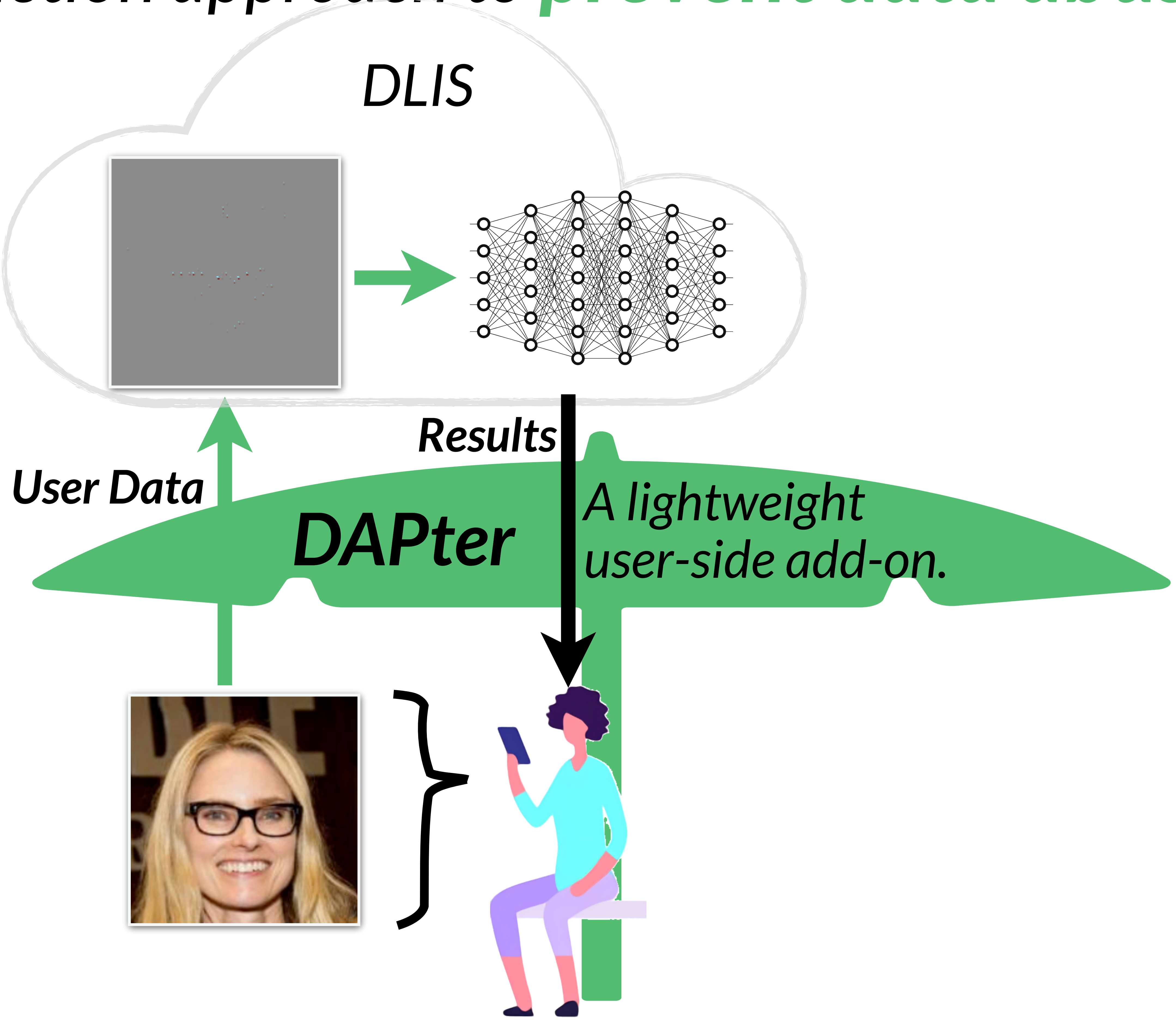

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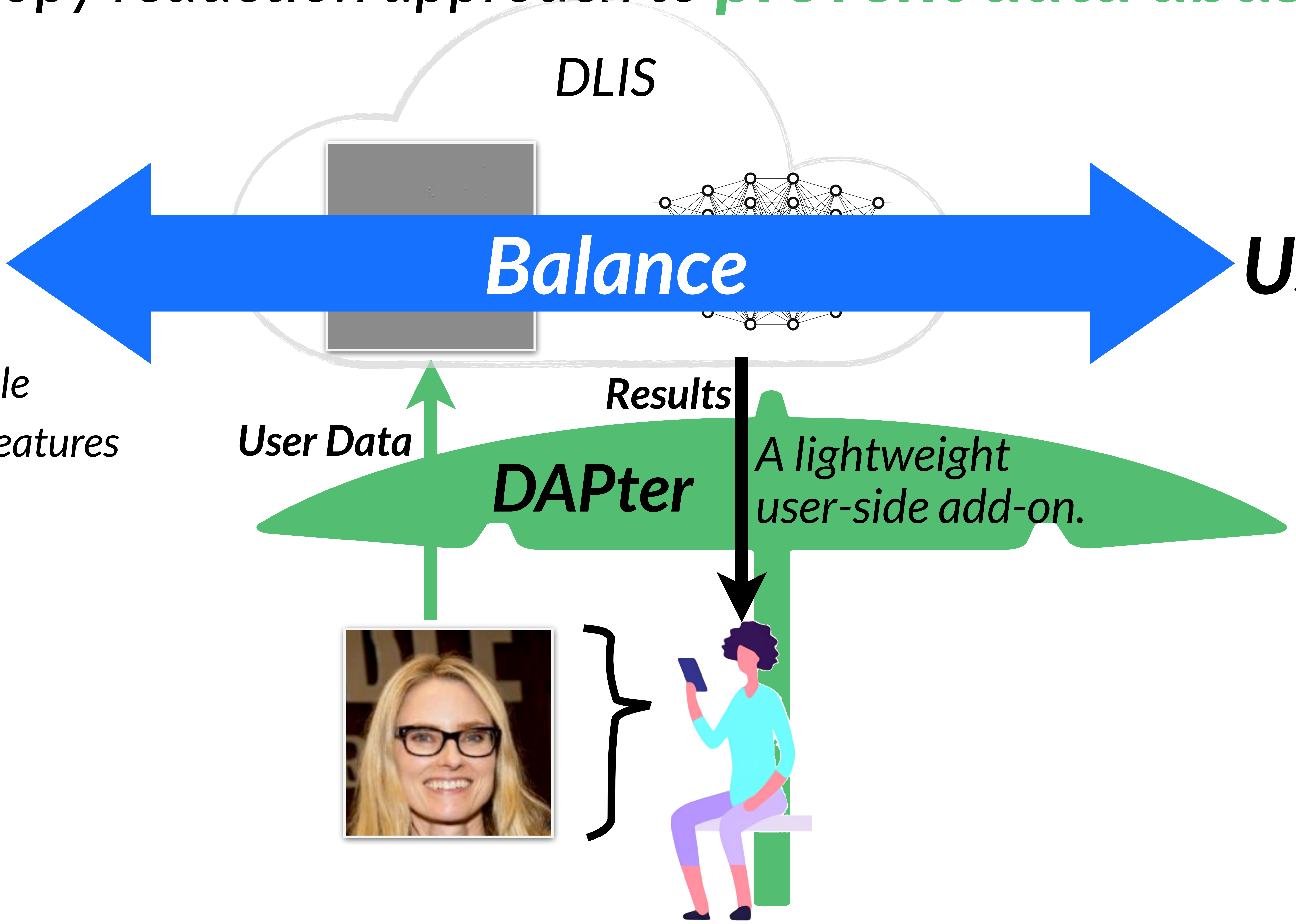


**Usability**

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*S2. Only retain necessary features*
*S3. Can't be reversed*

*U1. Maintain Accuracy*
*U2. No Changes*
*U3. Efficient*

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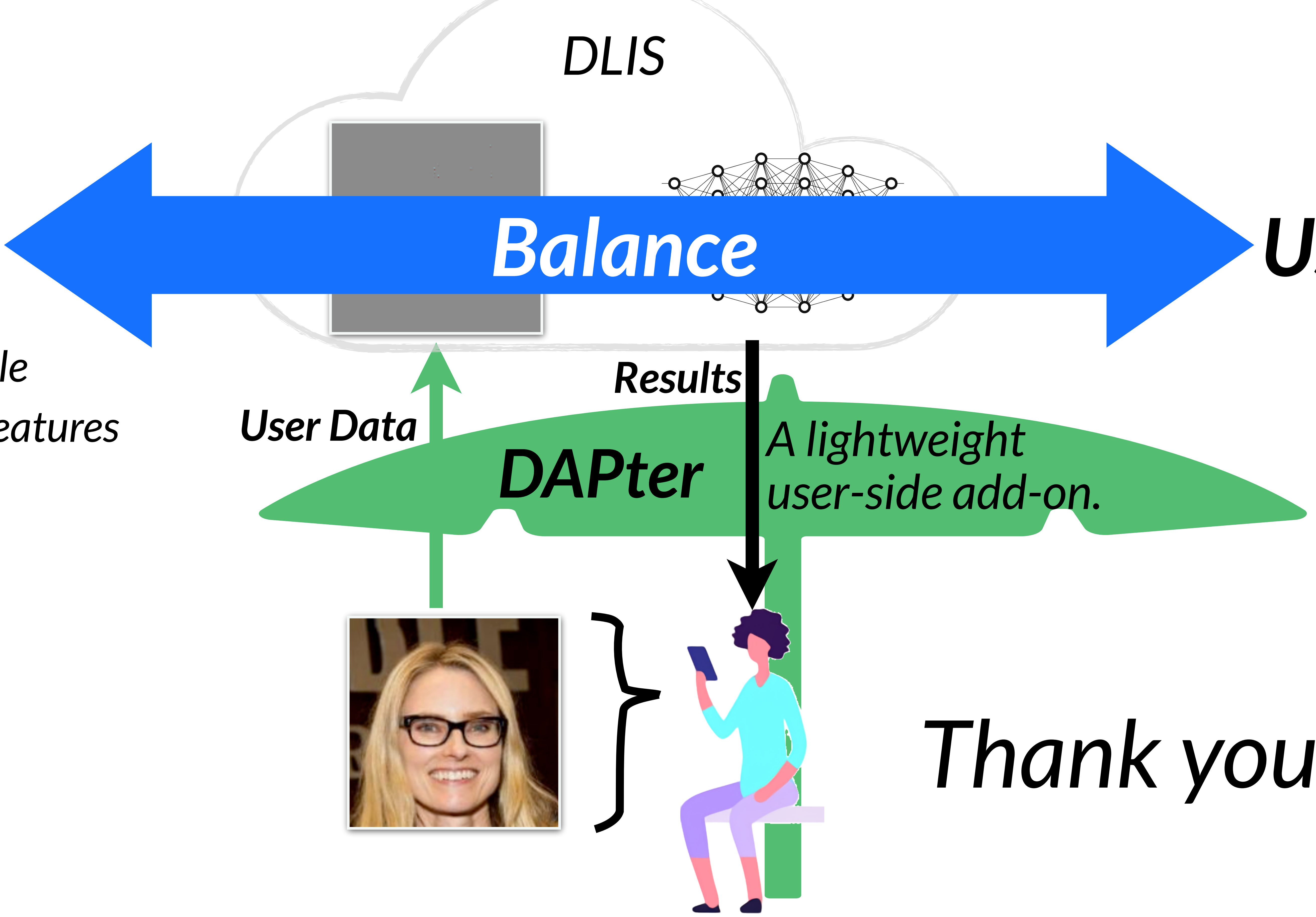


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*Thank you for attention!*