Relating ROC and CMC Curves

Work done with Brian DeCann

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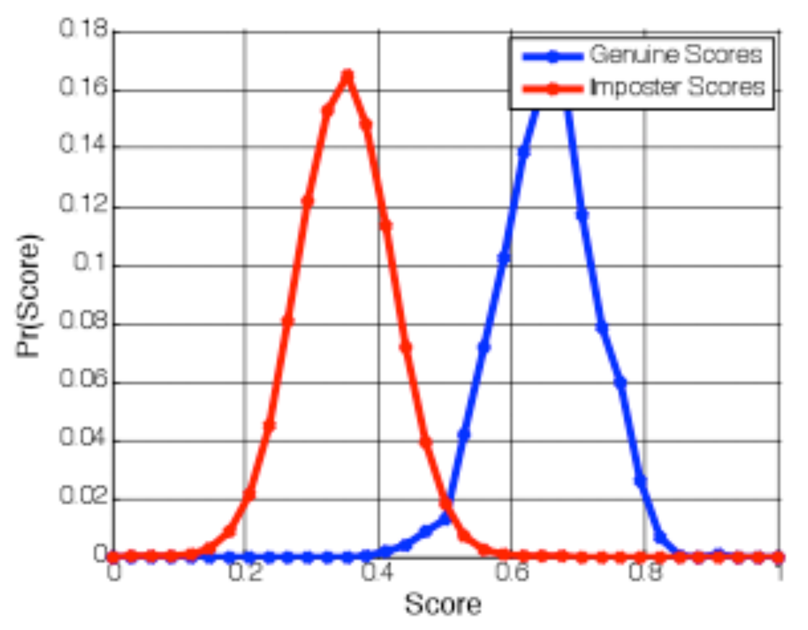
Introduction

- Performance of a verification system is summarized using Receiver Operating Characteristic (ROC) curve
- Performance of a closed-set identification system is summarized using Cumulative Match Characteristic (CMC) curve
- Can the CMC curve be derived from the ROC curve and vice-versa?

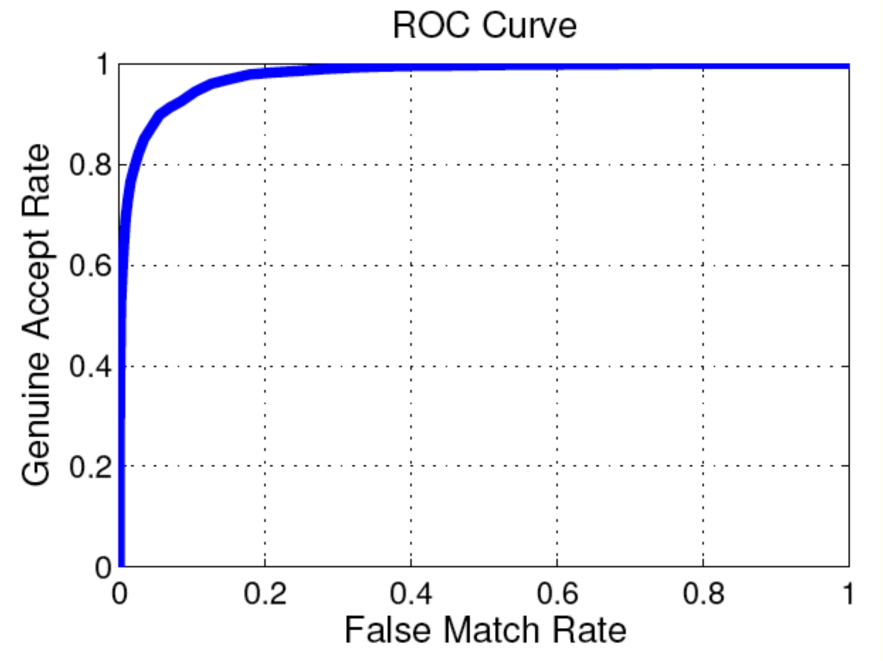
ROC Curve

- Biometrics samples are compared against each other
- Genuine and impostor scores are generated
- False Match Rate (FMR) and False Non-match Rate (FNMR) are computed at multiple thresholds
- ROC Curve: True Match Rate versus False Match Rate
- ROC Curve: Aggregate Statistics

ROC Curve



Match Score Distributions

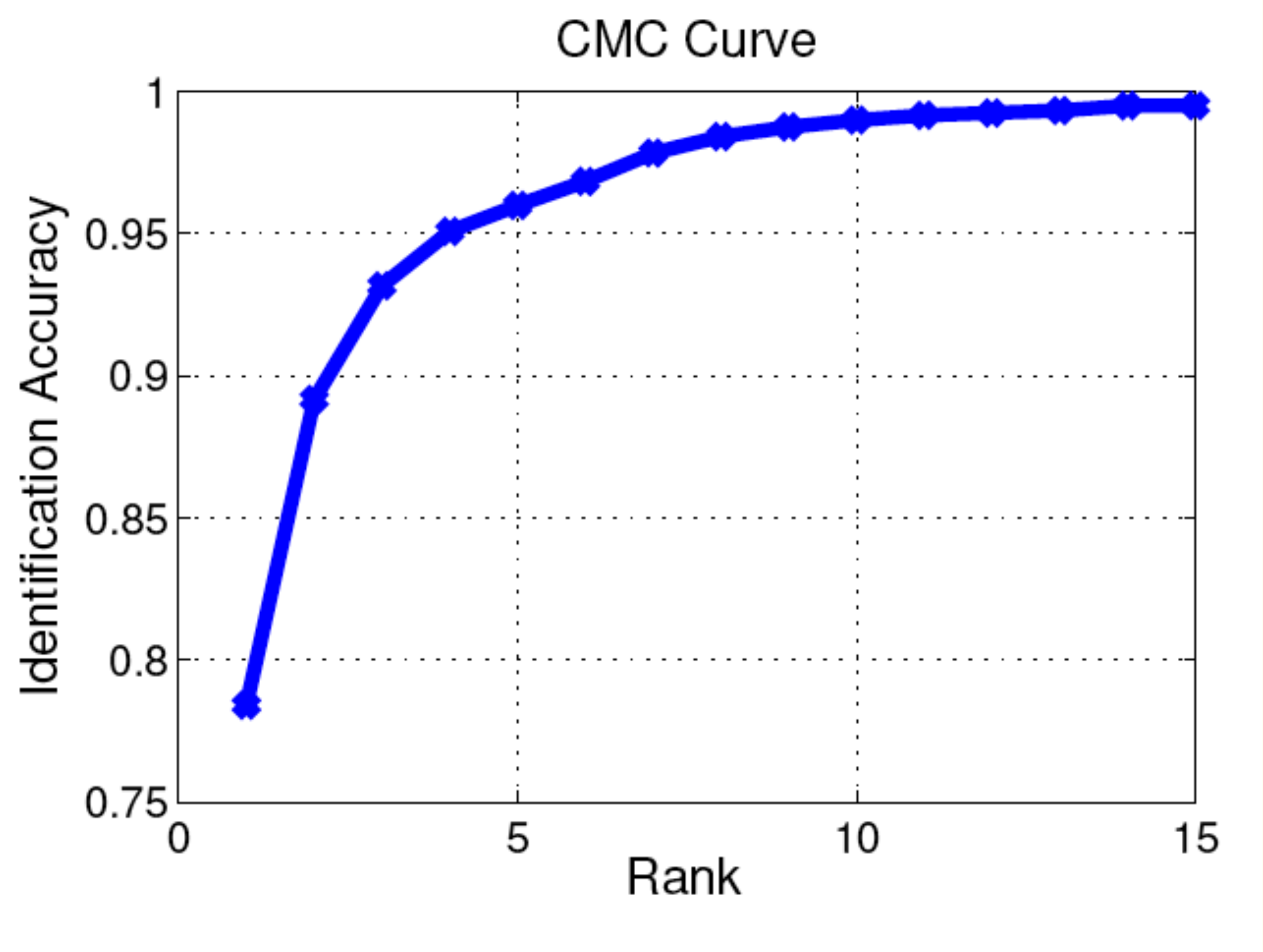


ROC Curve

CMC Curve

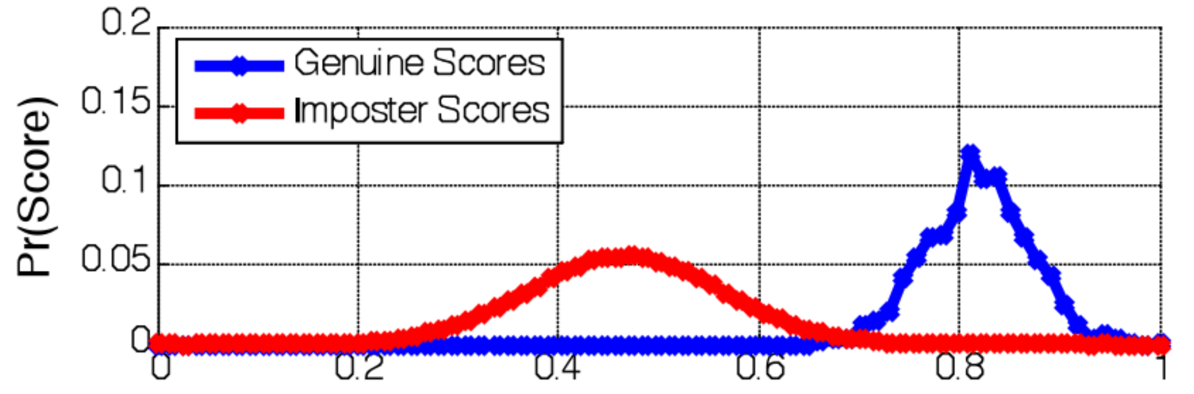
- Each probe biometric sample is compared against all gallery samples
- The resulting scores are sorted and ranked
- Determine the rank at which a true match occurs
- True Positive Identification Rate (TPIR): Probability of observing the correct identity within the top K ranks
- CMC Curve: Plots TPIR against ranks
- CMC Curve: Rank-based metric

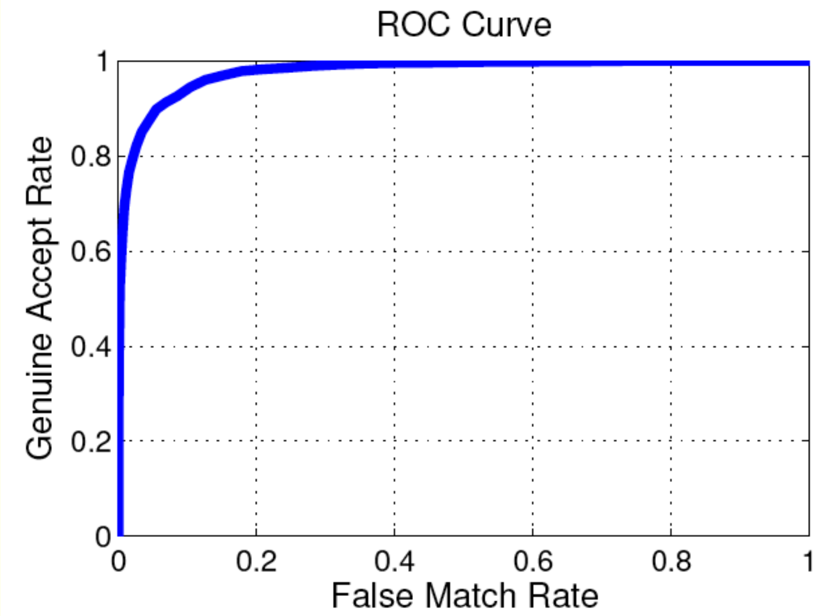
CMC Curve

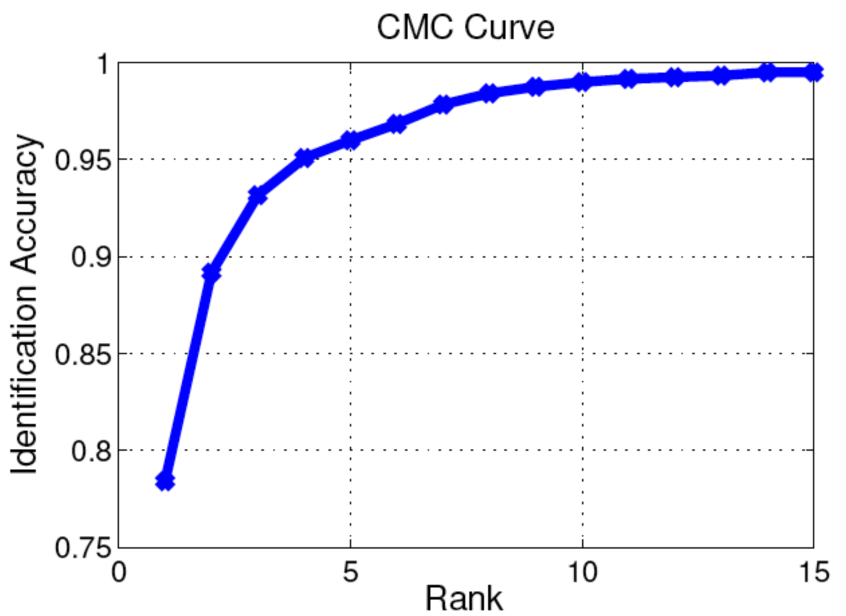

CMC Curve
Identification Accuracy
Rank
1
0.95
0.9
0.85
0.8
0.75
0
5
10
15

CMC versus ROC

- It is reasonable to expect a good ROC curve to be associated with a good CMC curve and vice-versa







Predicting CMC from ROC

- The CMC can be predicted from the ROC data
  - Bolle et. al. (2005), Hube (2006)

<u>Bolle</u>

$$Rank - n = \sum_{k=1}^{n} \binom{N-1}{k-1} \int_{0}^{\infty} F_G(s)\, FAR(s)^{k-1} \left(1 - FAR(s)\right)^{(N-k)} ds$$

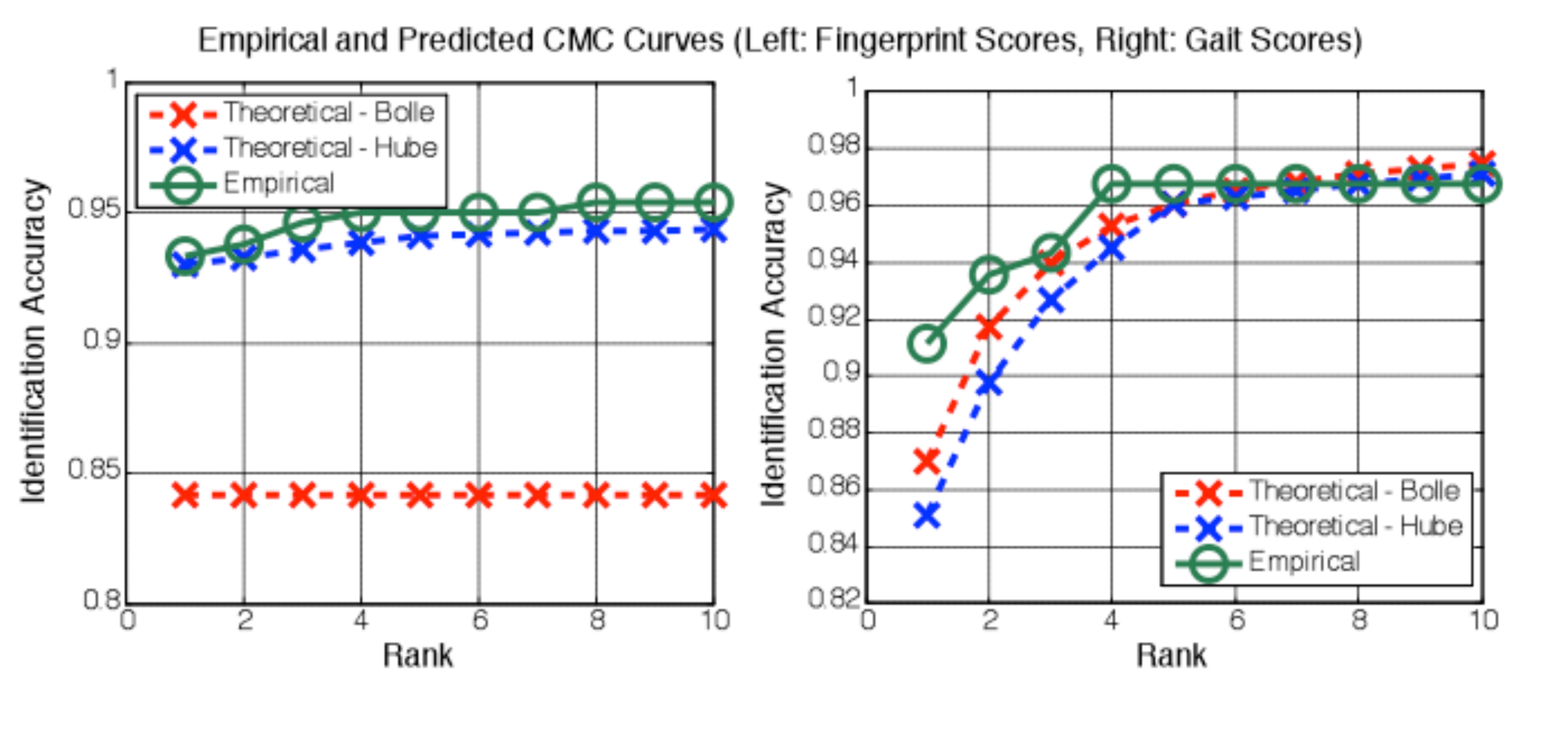
<u>Hube</u>

$$Rank - n = \mathrm{TPR}\left(\mathrm{FAR} = \frac{n}{N}\right), \text{ where TPR = (1-FNMR)}$$

- R. Bolle, J. Connell, S. Pankanti, N. Ratha, and A. Senior. *The Relation Between the ROC Curve and the CMC.* AutoID 2005
- J. Hube. *Using Biometric Verification to Estimate Identification Performance.* BSYM 2005

Predicting CMC from ROC

- But neither model perfectly predicts the empirical CMC curve



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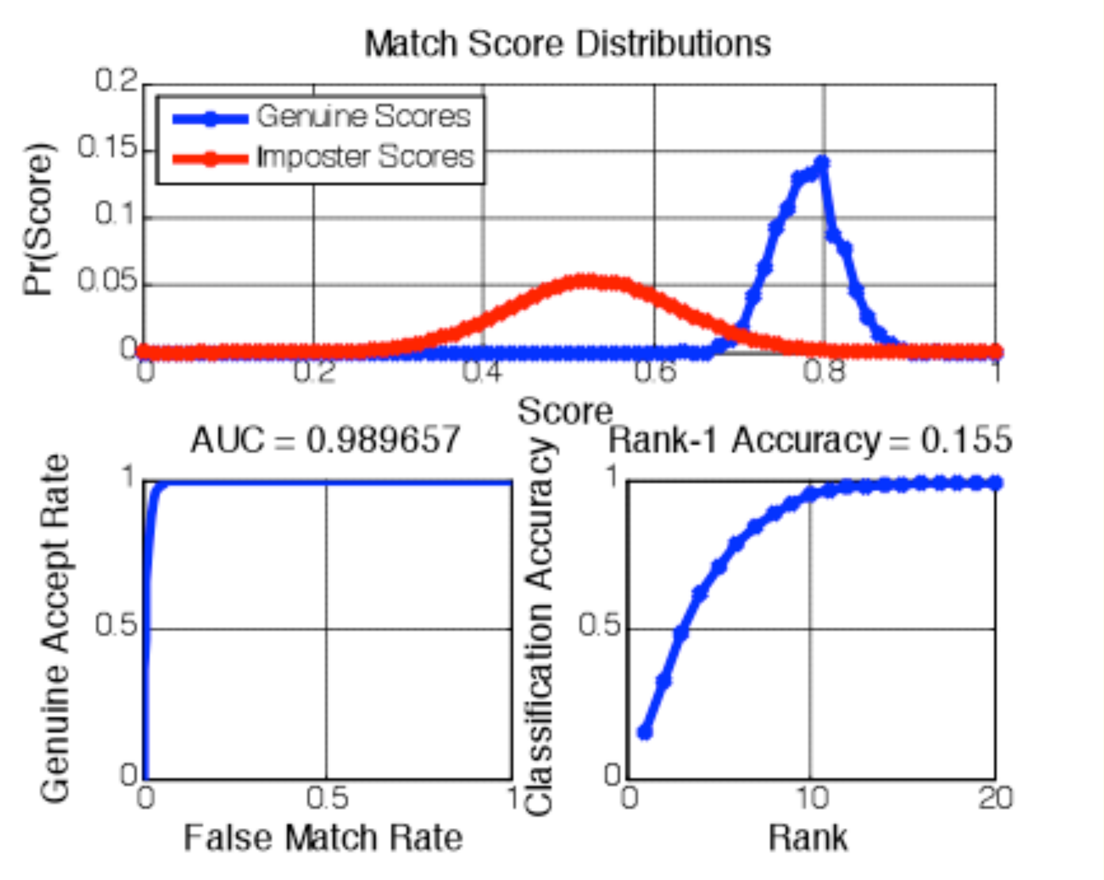
ROC versus CMC

- DeCann and Ross (2012) showed that it is possible for a good ROC curve to be associated with a poor CMC curve and vice-versa



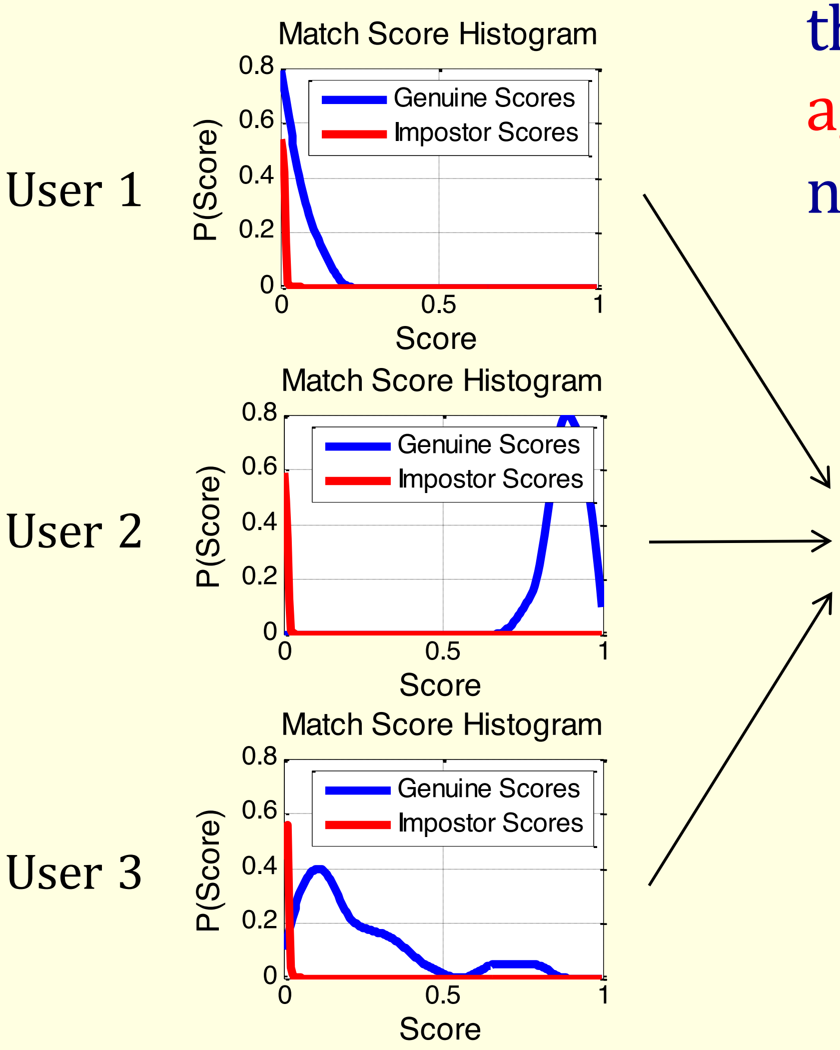
GOOD ROC CURVE

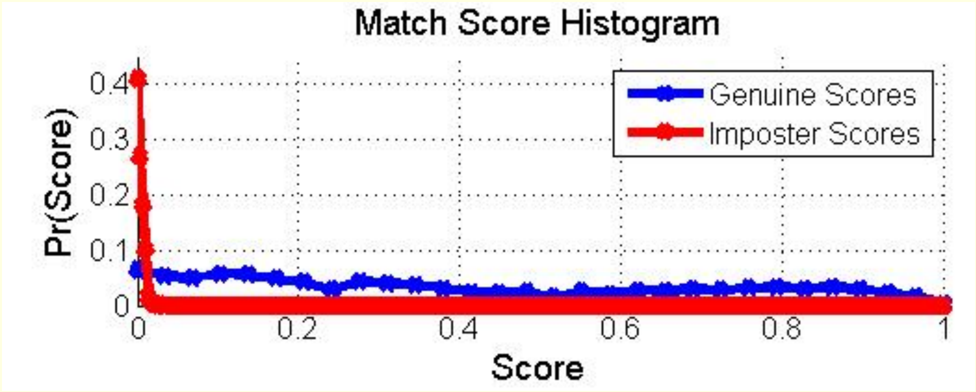
POOR CMC CURVE

B. Decann and A. Ross, "Can a Poor Verification System be a Good Identification System? A Preliminary Study," WIFS 2012

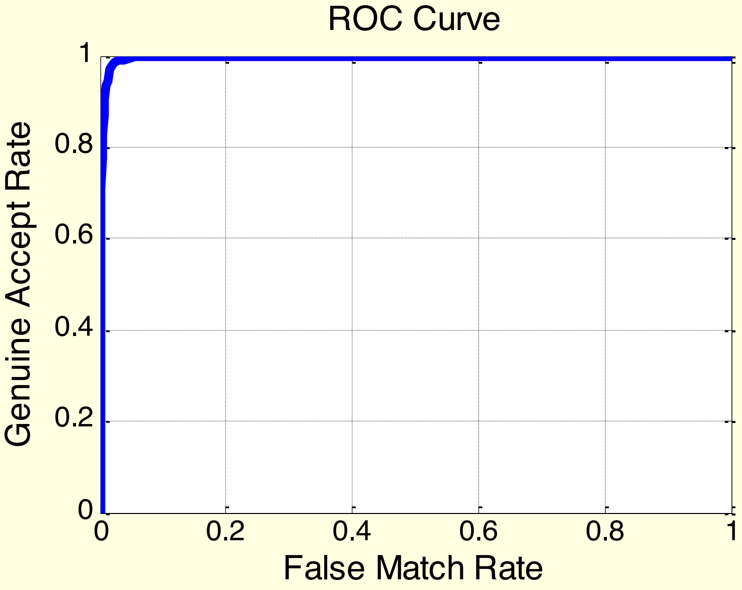
Why did CMC prediction models fail?

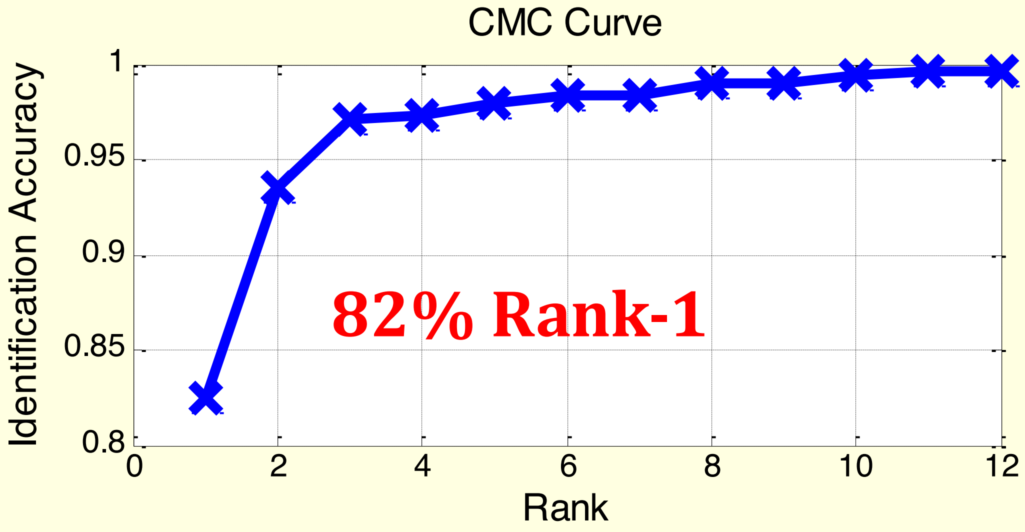
- Each identity contributes uniquely to the system performance, i.e., aggregate statistics do not necessarily predict ranked statistics



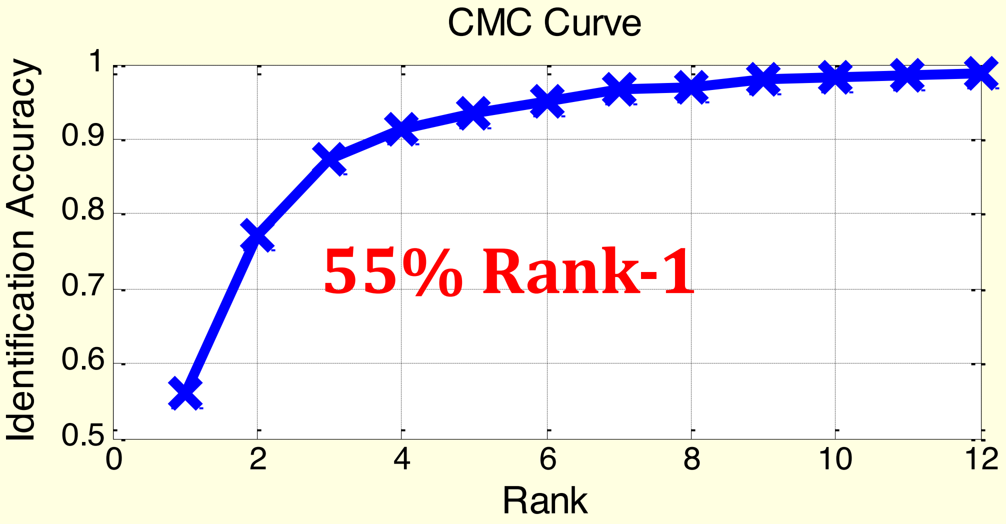


One ROC Curve: Multiple CMC Curves


ROC Curve


CMC Curve

82% Rank-1


CMC Curve

55% Rank-1

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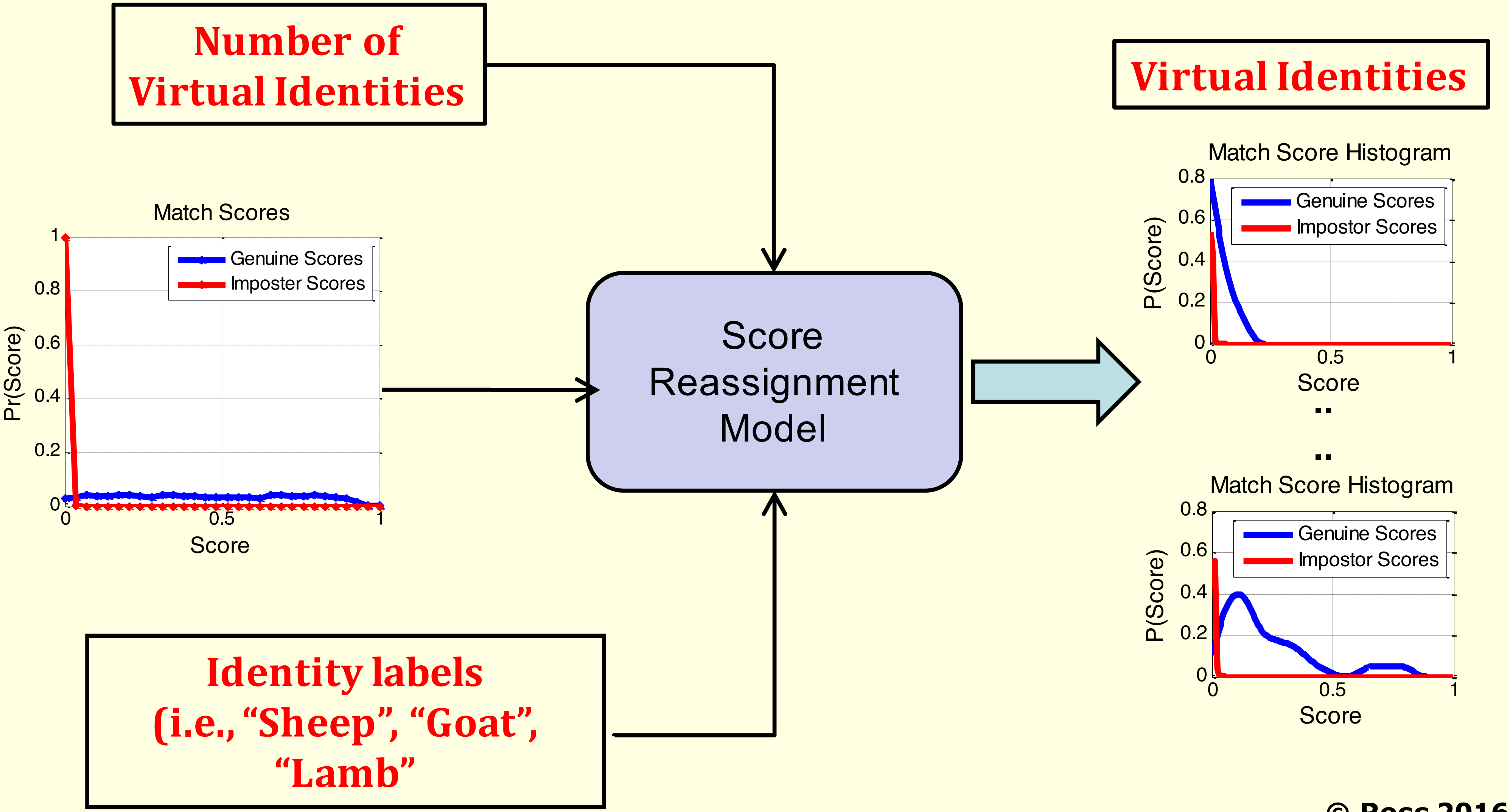
Virtual Identities

- Input: Set of genuine and impostor match scores
- Output: Virtual identities with different rank-based statistics
- Method: “Reassign” match scores to virtual identities according to the “Doddington’s Zoo” concept
  - Sheep: Low FMR and FNMR
  - Goats: High FNMR
  - Lambs: High FMR

Reassigning Match Scores

- Set of genuine and impostor match scores



Number of Virtual Identities

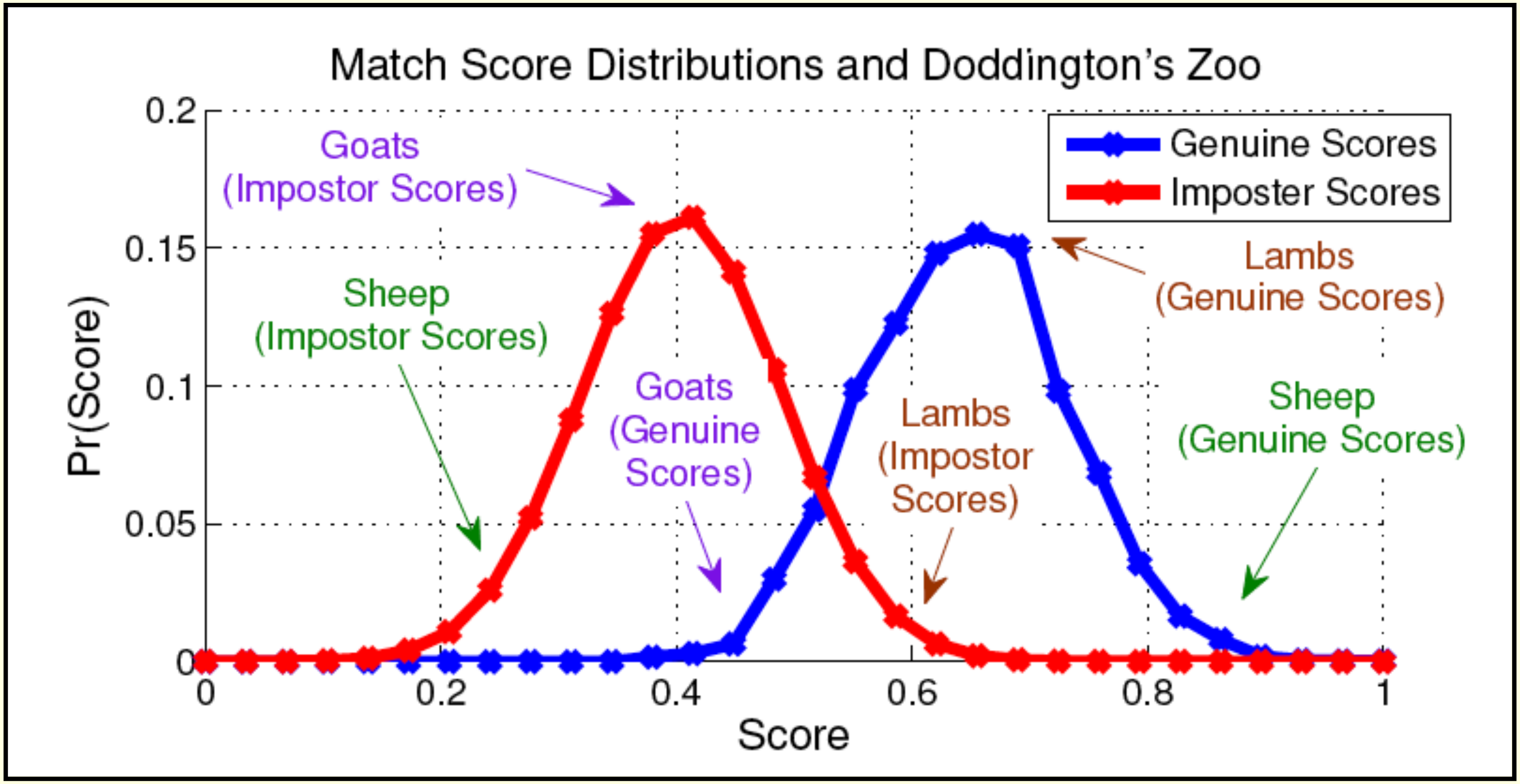
Score Reassignment Model

Virtual Identities

Identity labels (i.e., “Sheep”, “Goat”, “Lamb”

Sampling Match Scores

- Depending upon “Sheep”, “Goat”, “Lamb” labels



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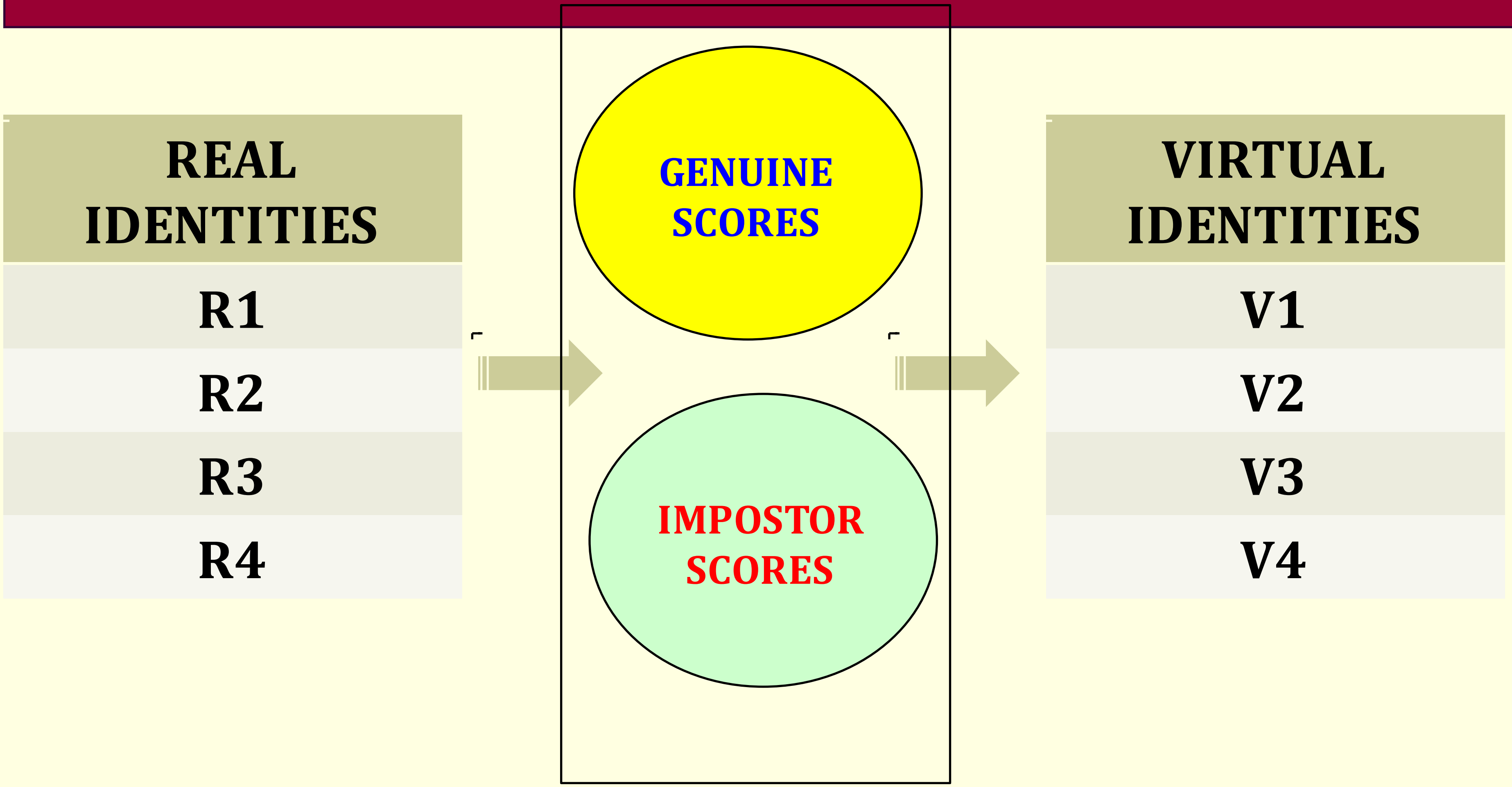
Sampling Rationale

- Genuine Scores: Use the label (“Sheep”, “Goat”, “Lamb”) to assign genuine match scores to a virtual identity
- Impostor Scores: Use the labels of “pairs” of virtual identities to assign impostor match scores to a virtual identity

From Real to Virtual



REAL IDENTITIES
R1
R2
R3
R4

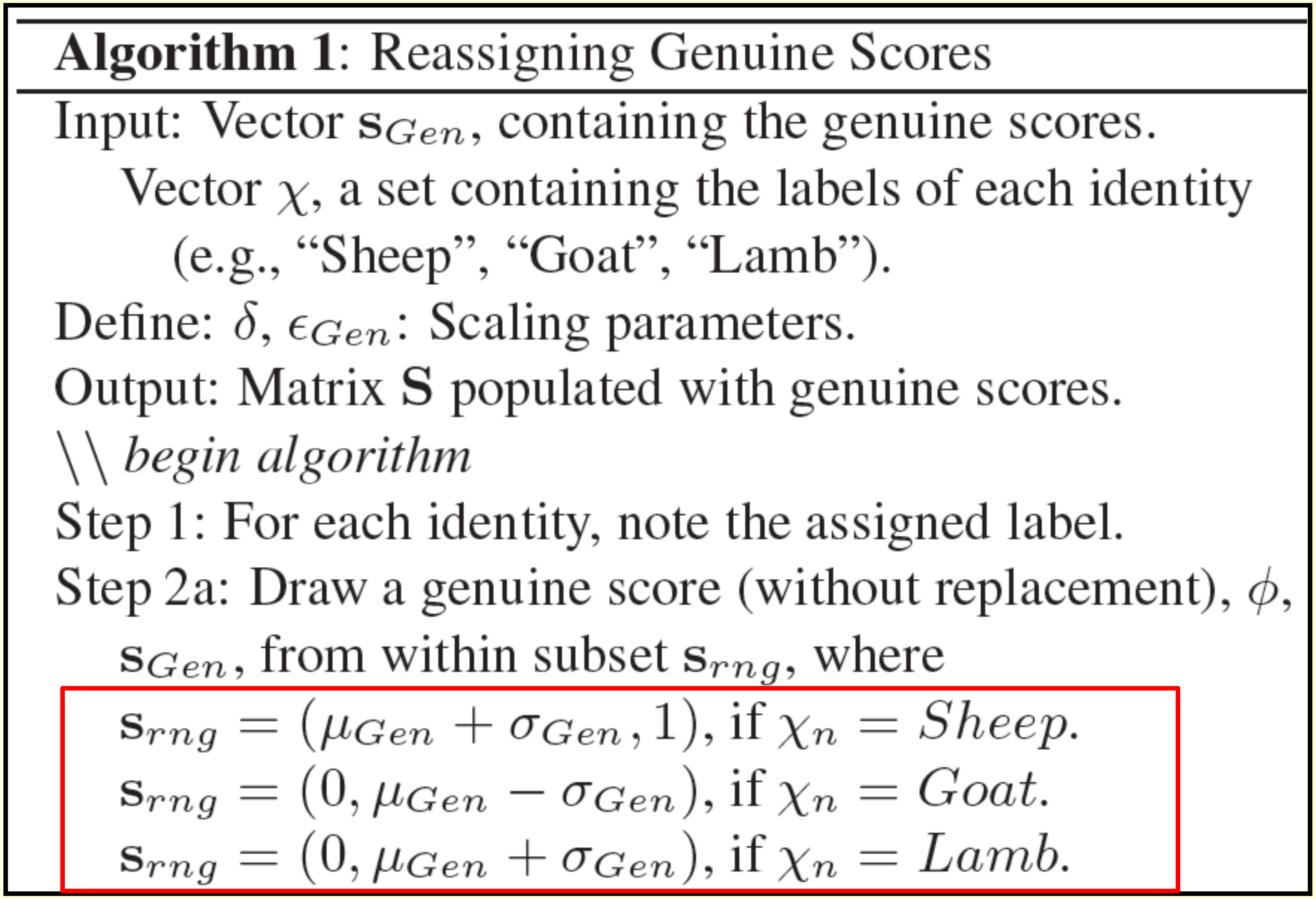
GENUINE SCORES

IMPOSTOR SCORES

VIRTUAL IDENTITIES
V1
V2
V3
V4

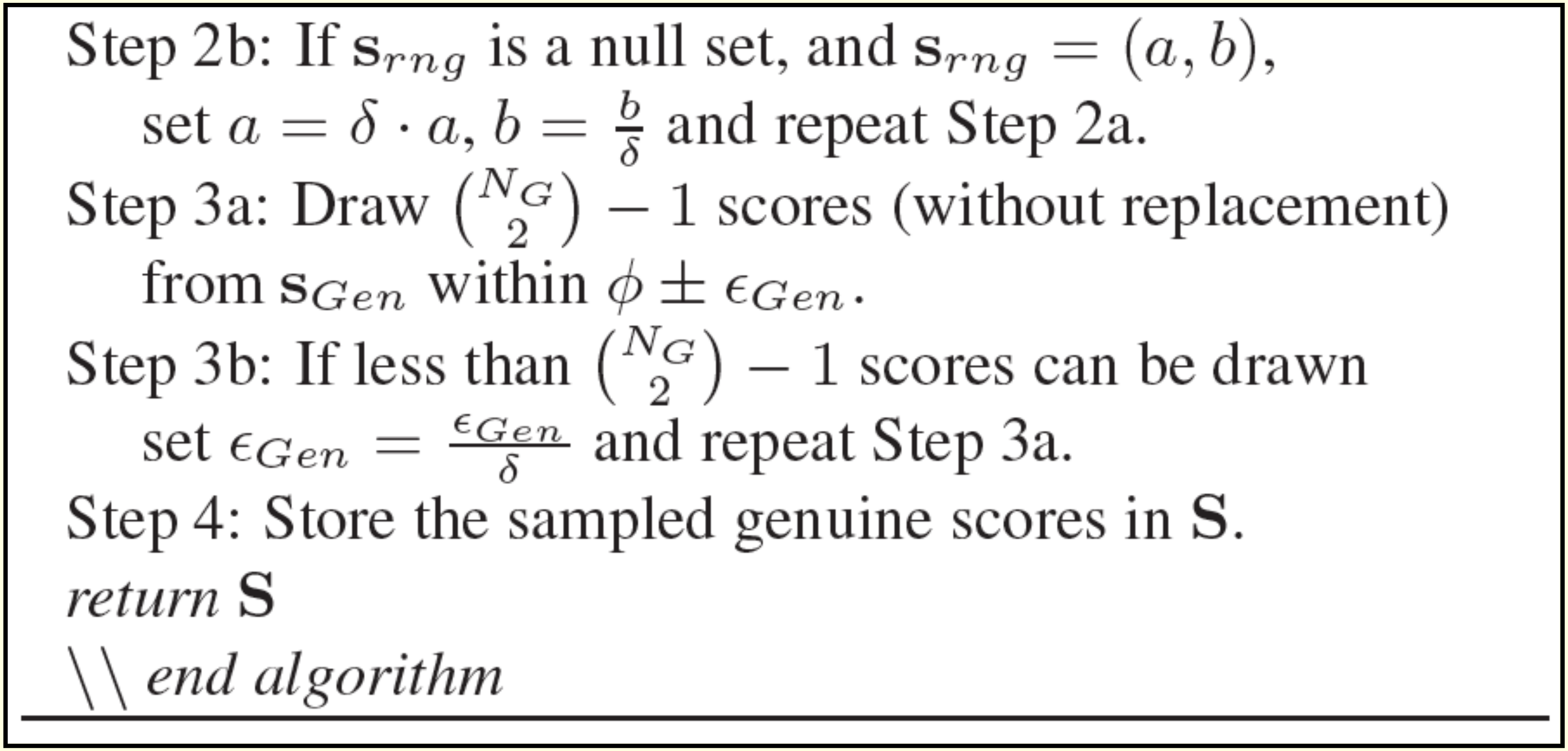
- **Aggregate Statistics do not change**

Reassigning Genuine Scores



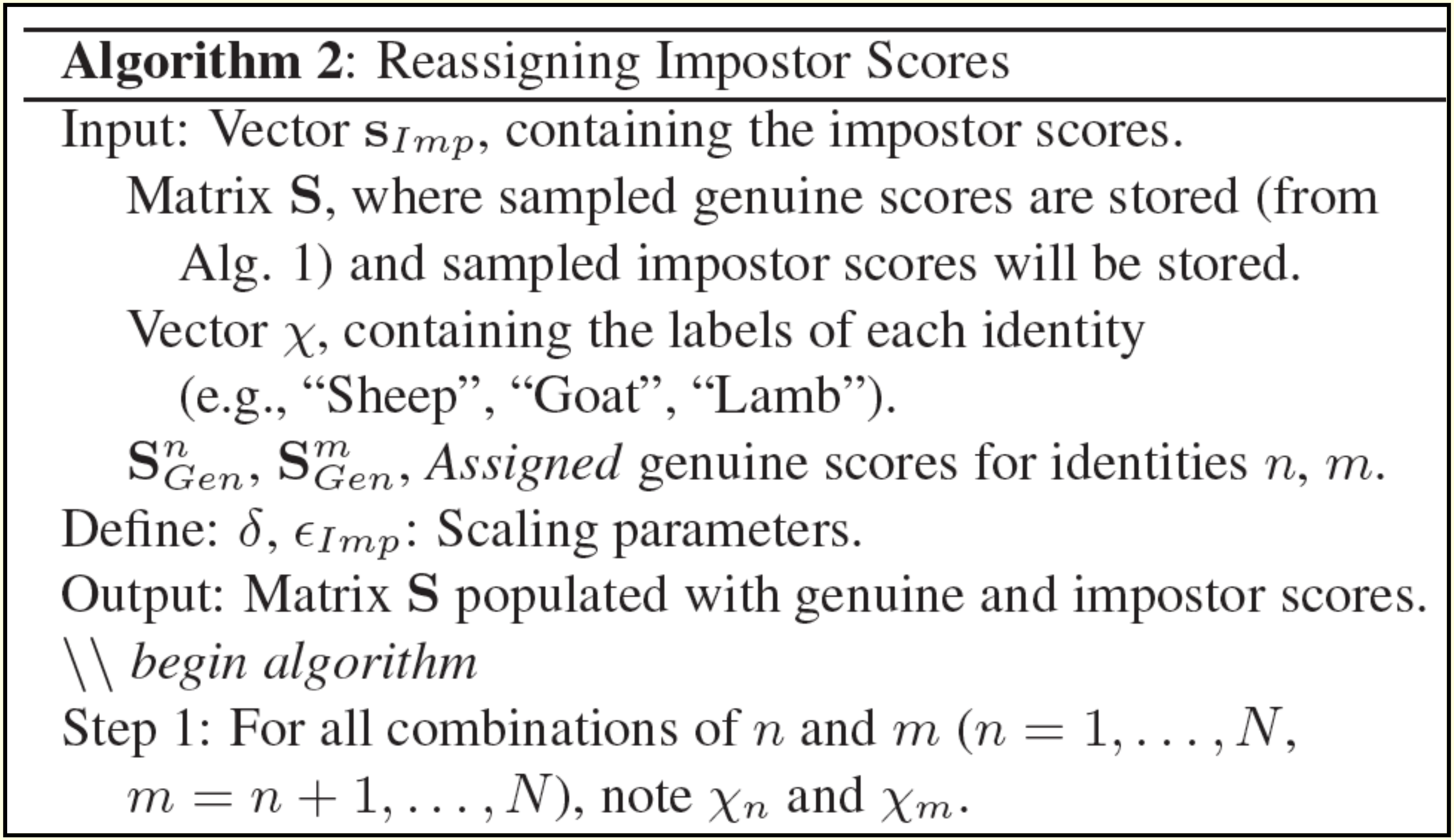
```
Algorithm 1: Reassigning Genuine Scores
Input: Vector $\mathbf{s}_{Gen}$, containing the genuine scores.
    Vector $\chi$, a set containing the labels of each identity
        (e.g., “Sheep”, “Goat”, “Lamb”).
Define: $\delta$, $\epsilon_{Gen}$: Scaling parameters.
Output: Matrix $\mathbf{S}$ populated with genuine scores.
\\ begin algorithm
Step 1: For each identity, note the assigned label.
Step 2a: Draw a genuine score (without replacement), $\phi$,
    $\mathbf{s}_{Gen}$, from within subset $\mathbf{s}_{rng}$, where
    $\mathbf{s}_{rng} = (\mu_{Gen} + \sigma_{Gen}, 1)$, if $\chi_n = Sheep$.
    $\mathbf{s}_{rng} = (0, \mu_{Gen} - \sigma_{Gen})$, if $\chi_n = Goat$.
    $\mathbf{s}_{rng} = (0, \mu_{Gen} + \sigma_{Gen})$, if $\chi_n = Lamb$.
```

Reassigning Genuine Scores



```
Step 2b: If $\mathbf{s}_{rng}$ is a null set, and $\mathbf{s}_{rng} = (a, b)$,
    set $a = \delta \cdot a$, $b = \frac{b}{\delta}$ and repeat Step 2a.
Step 3a: Draw $\binom{N_G}{2} - 1$ scores (without replacement)
    from $\mathbf{s}_{Gen}$ within $\phi \pm \epsilon_{Gen}$.
Step 3b: If less than $\binom{N_G}{2} - 1$ scores can be drawn
    set $\epsilon_{Gen} = \frac{\epsilon_{Gen}}{\delta}$ and repeat Step 3a.
Step 4: Store the sampled genuine scores in $\mathbf{S}$.
return $\mathbf{S}$
\\ end algorithm
```

Reassigning Impostor Scores



```
**Algorithm 2**: Reassigning Impostor Scores
Input: Vector $\mathbf{s}_{Imp}$, containing the impostor scores.
    Matrix $\mathbf{S}$, where sampled genuine scores are stored (from
        Alg. 1) and sampled impostor scores will be stored.
    Vector $\chi$, containing the labels of each identity
        (e.g., "Sheep", "Goat", "Lamb").
    $\mathbf{S}^{n}_{Gen}$, $\mathbf{S}^{m}_{Gen}$, *Assigned* genuine scores for identities $n$, $m$.
Define: $\delta$, $\epsilon_{Imp}$: Scaling parameters.
Output: Matrix $\mathbf{S}$ populated with genuine and impostor scores.
\\ *begin algorithm*
Step 1: For all combinations of $n$ and $m$ ($n = 1, \ldots, N$,
    $m = n + 1, \ldots, N$), note $\chi_n$ and $\chi_m$.
```

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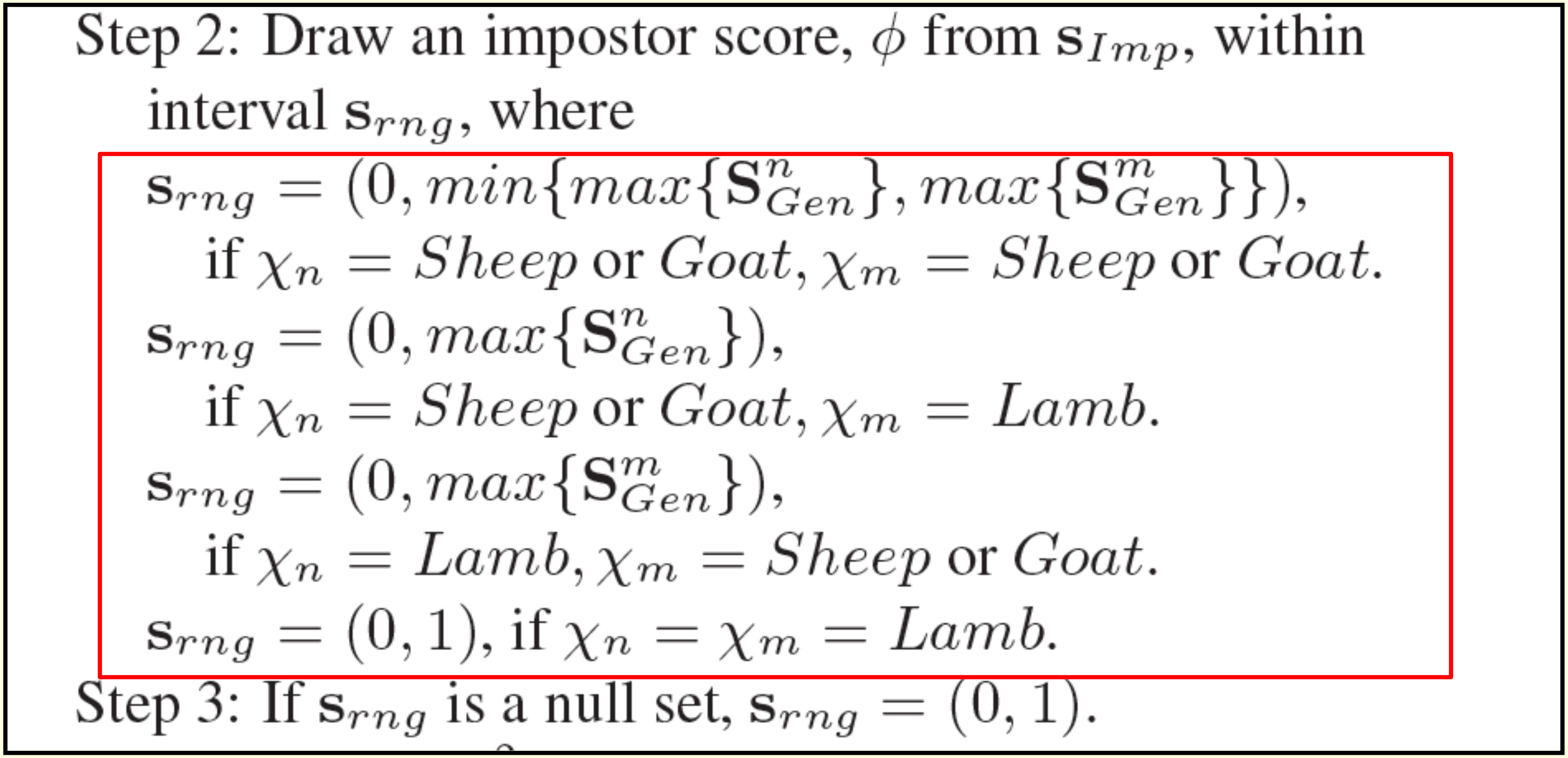
Reassigning Impostor Scores

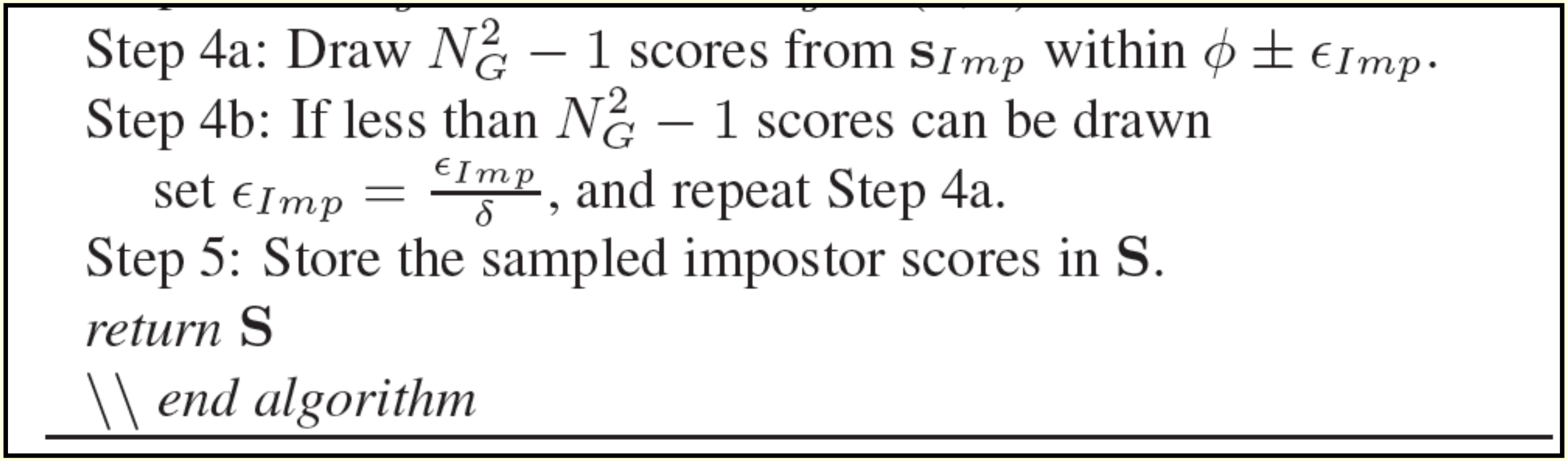


Step 2: Draw an impostor score, ϕ from $\mathbf{s}_{Imp}$, within interval $\mathbf{s}_{rng}$, where

$$\mathbf{s}_{rng} = (0, min\{max\{\mathbf{S}^{n}_{Gen}\}, max\{\mathbf{S}^{m}_{Gen}\}\}),$$
$$\text{if } \chi_n = Sheep \text{ or } Goat, \chi_m = Sheep \text{ or } Goat.$$
$$\mathbf{s}_{rng} = (0, max\{\mathbf{S}^{n}_{Gen}\}),$$
$$\text{if } \chi_n = Sheep \text{ or } Goat, \chi_m = Lamb.$$
$$\mathbf{s}_{rng} = (0, max\{\mathbf{S}^{m}_{Gen}\}),$$
$$\text{if } \chi_n = Lamb, \chi_m = Sheep \text{ or } Goat.$$
$$\mathbf{s}_{rng} = (0, 1), \text{ if } \chi_n = \chi_m = Lamb.$$

Step 3: If $\mathbf{s}_{rng}$ is a null set, $\mathbf{s}_{rng} = (0, 1)$.

Reassigning Impostor Scores

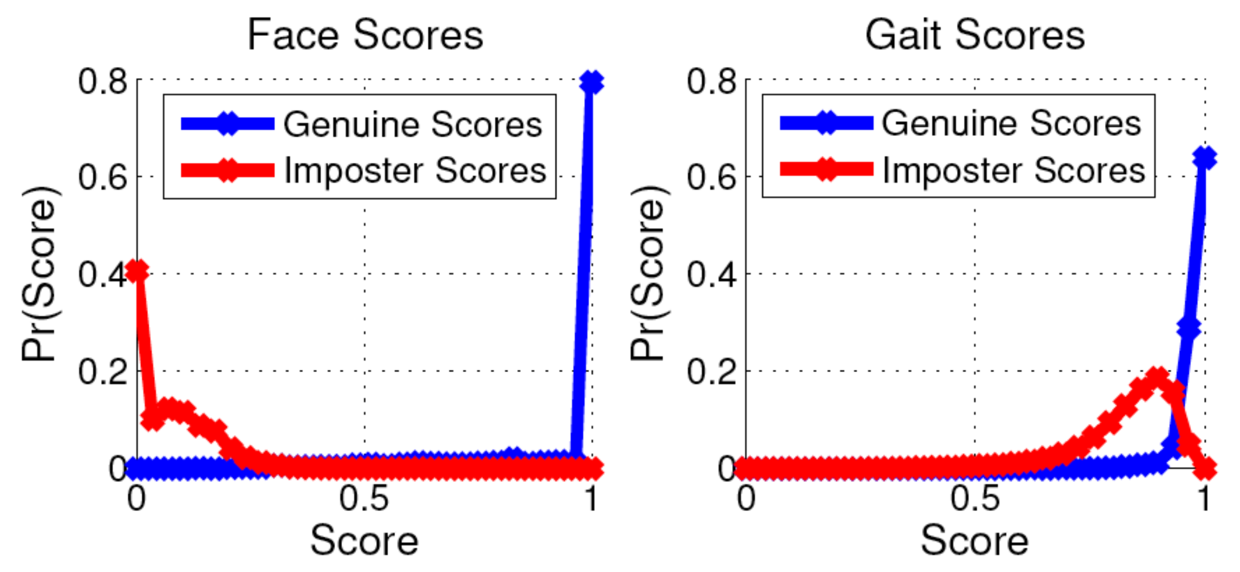


```
Step 4a: Draw $N_G^2 - 1$ scores from $\mathbf{s}_{Imp}$ within $\phi \pm \epsilon_{Imp}$.
Step 4b: If less than $N_G^2 - 1$ scores can be drawn
    set $\epsilon_{Imp} = \frac{\epsilon_{Imp}}{\delta}$, and repeat Step 4a.
Step 5: Store the sampled impostor scores in $\mathbf{S}$.
return $\mathbf{S}$
\\ end algorithm
```

Datasets Used

- **Face: WVU Multimodal Dataset**
  - **240 subjects, 5 Samples / subject**
  - **Match scores computed using VeriLook**

- **Gait: CASIA B dataset**
  - **124 subjects, 6 samples / subject**
  - **Match scores computed using Gait Curves algorithm**



Evaluation Criteria

- ROC data: Area underneath the ROC (AUC)
- CMC data: Weighted Rank-M strategy

Generate Virtual Identities

- Generate virtual identities with different input parameters: (% Sheep, % Goats, % Lambs)
- Compute AUC and Rank-M values

Sheep (%)	Goat (%)	Lambs (%)	AUC (Face)	Rank-M (Face)	AUC (Gait)	Rank-M (Gait)
100	0	0	0.999	1.0	0.980	1.0
82	10	8	0.999	1.0	0.980	0.966
50	26	24	0.999	0.997	0.980	0.915
15	10	75	0.999	0.997	0.980	0.800

Same Aggregate Statistics

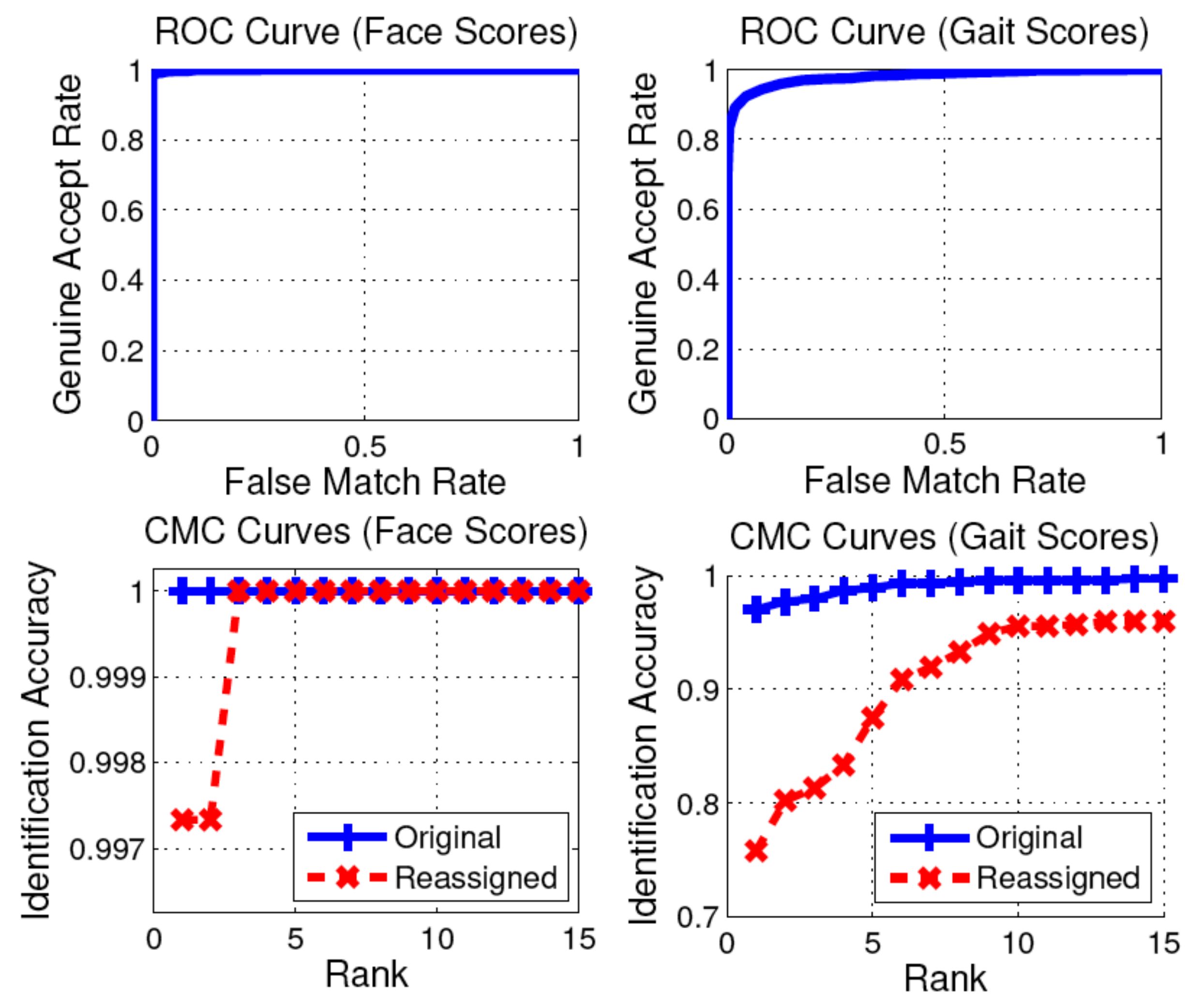
Different Rank Statistics

Note: *Increasing* the proportion of Goats or Lambs *decreases* Rank-M performance

A Closer Look

- ROC and CMC curves for “Original” and “Reassigned”
- (15% Sheep, 10% Goats, 75% Lambs)

100% to 99.7%



99% to 75%

Summary

- It is possible for a single ROC curve to be associated with multiple CMC curves
- The distribution of "Sheep", "Goat", "Lamb" in the target population results in this phenomenon
- Any ROC-CMC prediction model, should account for this variability in user performance
- Soft biometric traits are more likely to exhibit this type of disparity
- Reporting both ROC and CMC curves is recommended
- Note: Closed-set identification

Project sponsored by ONR

Reading Material

- B. DeCann and A. Ross, "**Relating ROC and CMC Curves via the Biometric Menagerie**," Proc. of 6th IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS), (Washington DC, USA), September 2013
- B. Decann and A. Ross, "**Can a Poor Verification System be a Good Identification System? A Preliminary Study**," Proc. of IEEE International Workshop on Information Forensics and Security (WIFS), (Tenerife, Spain), December 2012