Multibiometrics

COMP 388-002/488-002 Biometrics

Daniel Moreira

Fall 2023

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Today you will…

Get to know
Importance of Multibiometrics.

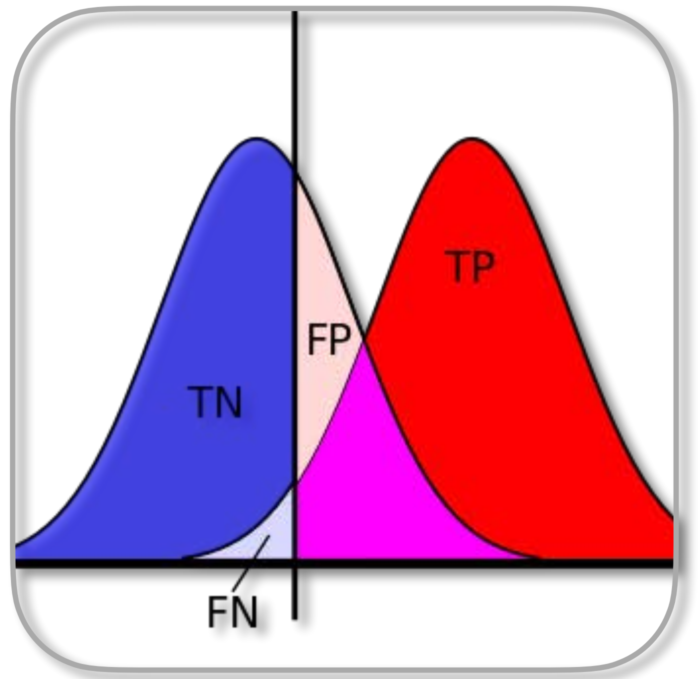
Today's attendance

Please fill out the form

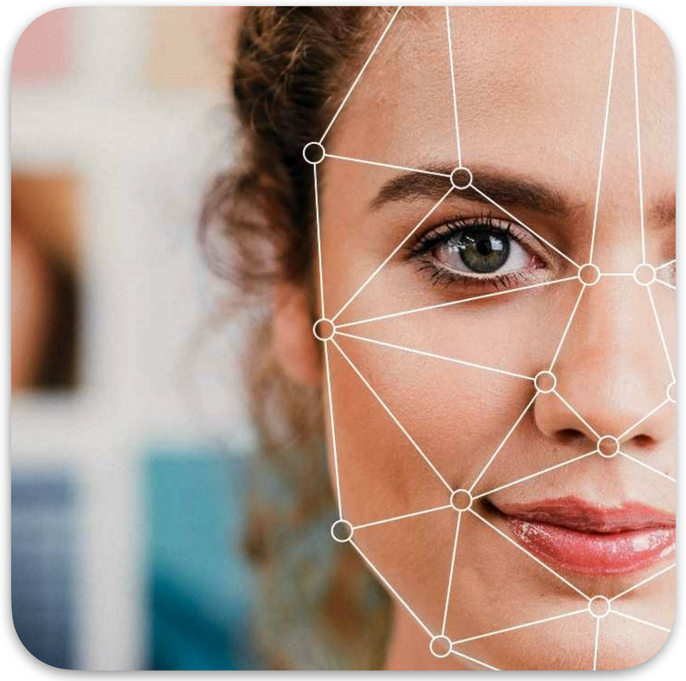
https://forms.gle/iBBzE9qMPd9LCCaw6

Course Overview

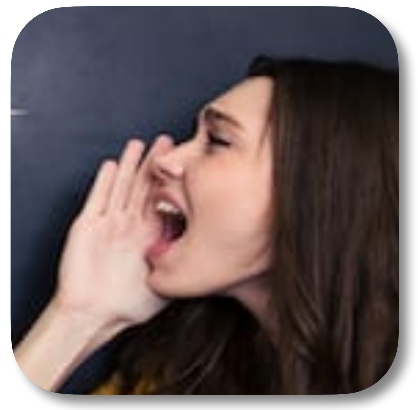
Content



Basics
Concepts
Metrics
Metric implementation



Core Traits (3)
Concepts
Baseline implementation
Data collection
Evaluation
Attacks
Assignments



Alternative Traits and Fusion
Concepts

Invited Talks (2)
State of the art
Future work

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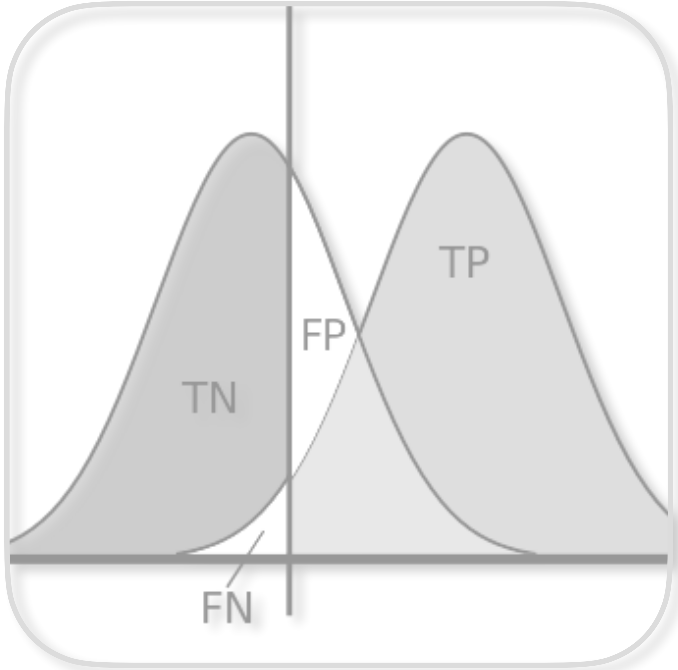
Course Overview

Fusion (a.k.a. Multibiometrics)



Basics
Concepts
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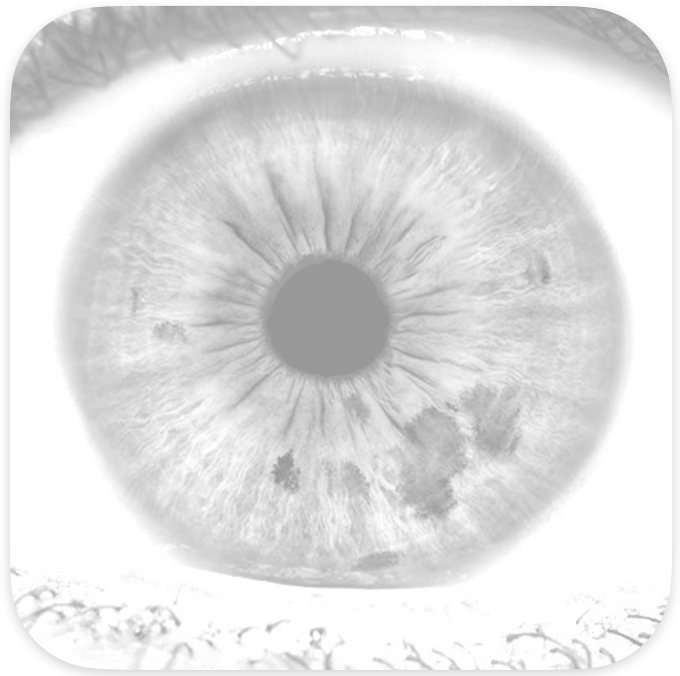
Metric implementation



Core Traits (3)
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Baseline implementation
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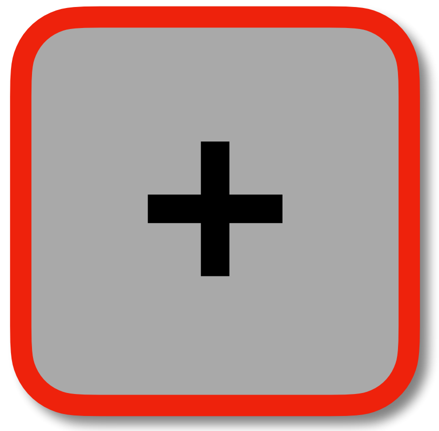

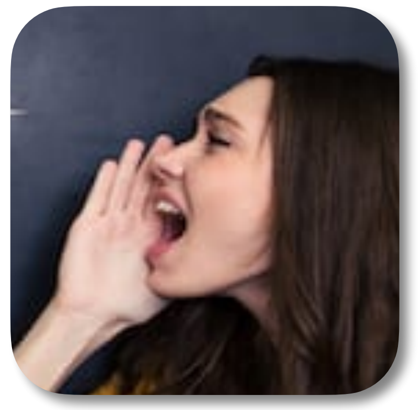

Alternative Traits and Fusion
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Multibiometrics

Pick a Trait

Universality (1/8)
Does everybody have the trait?

Uniqueness (2/8)
How likely two or more individuals will present the same trait?

Permanence (3/8)
How easily does the trait change?

Measurability (4/8)
How easy is it to acquire and digitize the trait?

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Multibiometrics

Pick a Trait

Acceptability (5/8)
Will individuals collaborate during data collection?

Circumvention (6/8)
How hard can the trait be forged or imitated?

Performance (7/8)
How good is the trait quantitatively
according to objective metrics?

Accountability (8/8)
How easy is it for the everyman to understand the trait comparison?

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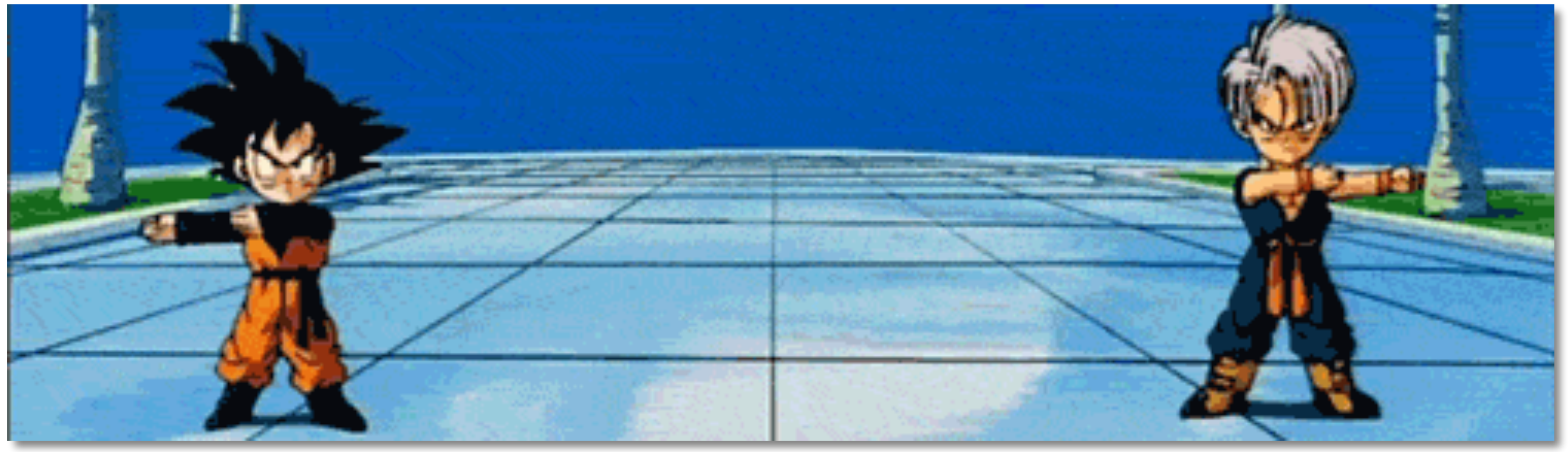
Multibiometrics

Pick a Trait

There is no silver bullet.
No trait satisfies all *concepts*.

Multibiometrics

Solution
Rely on multiple traits.
Allow various presentations.
Combine results (data fusion).



Pros
More concepts can be satisfied.
System is more robust to attacks.
It becomes more expensive
to attack the system.

Cons
System becomes more expensive
(more sensors, more software).
More runtime.
More complexity.

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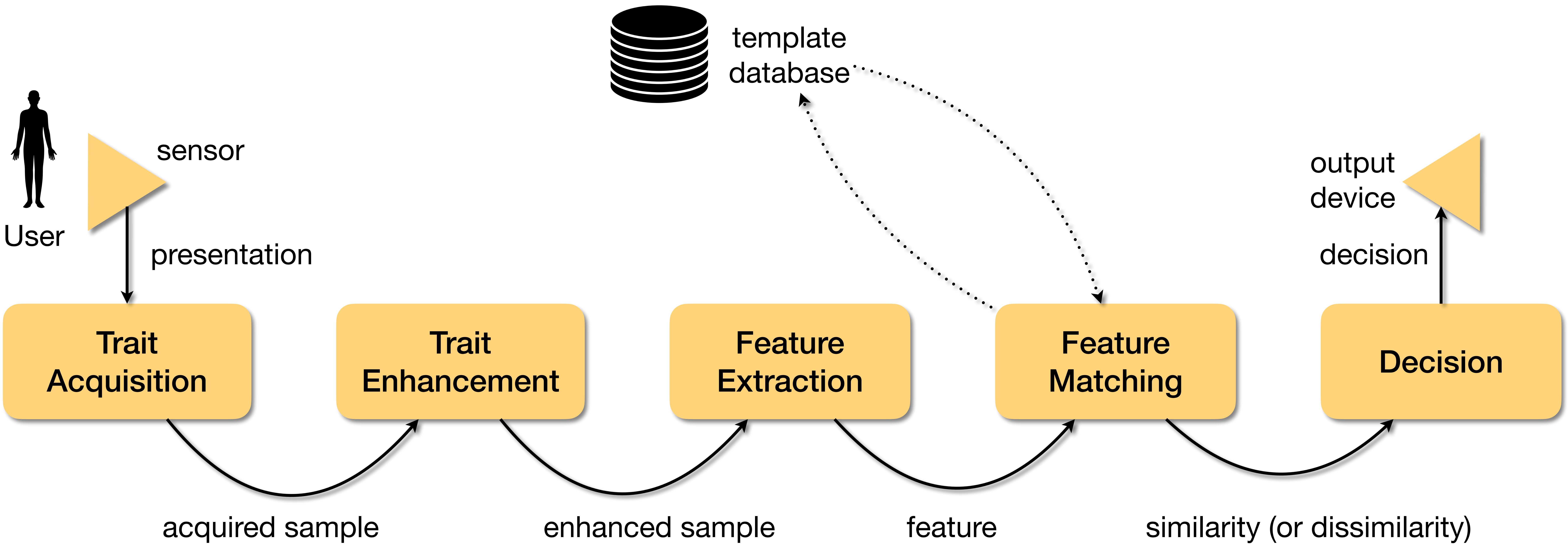
Multibiometrics

Types of Multibiometric Systems



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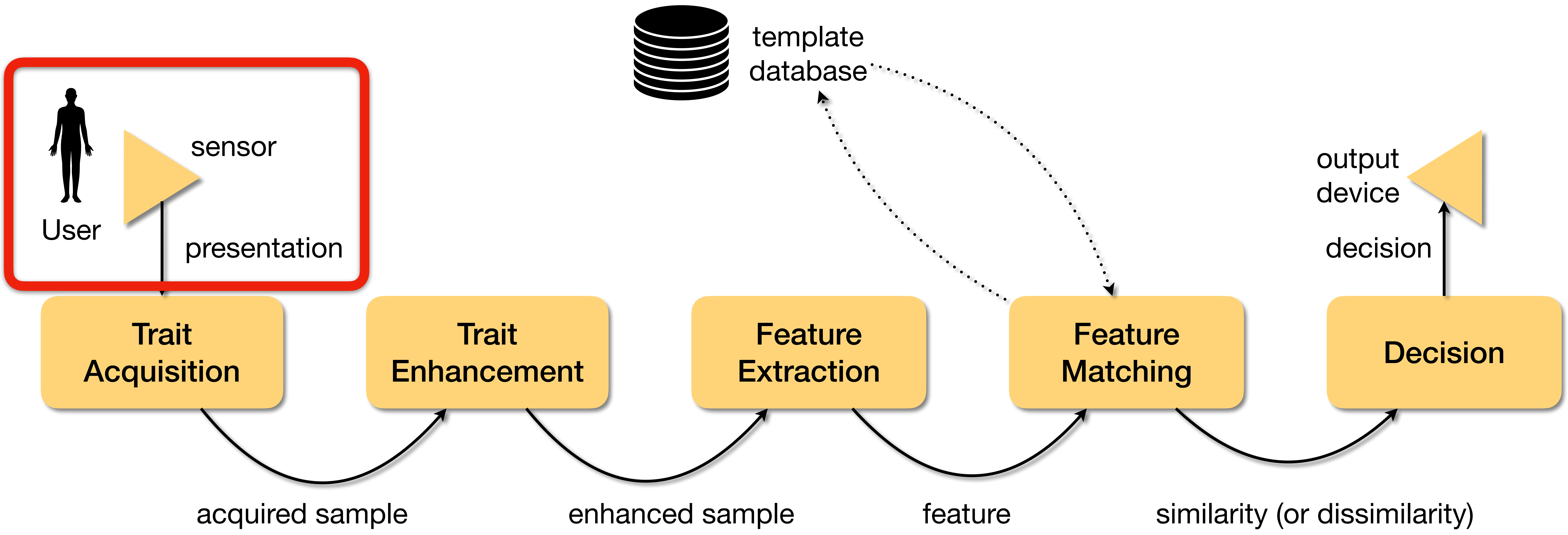
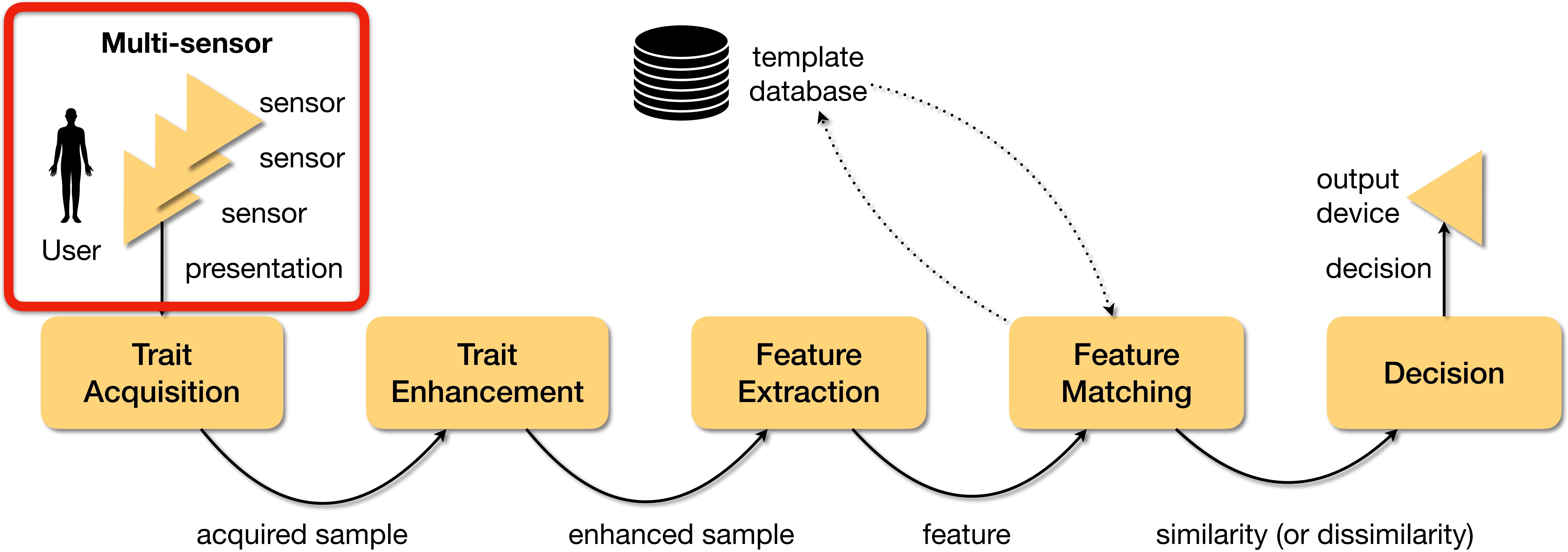
Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems



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Multibiometrics

Types of Multibiometric Systems

Dr. Walter Scheirer

Multi-sensor Systems (1/5)
Single trait, multiple sensors.

If one sensor fails, other sensors might overcome the failure.

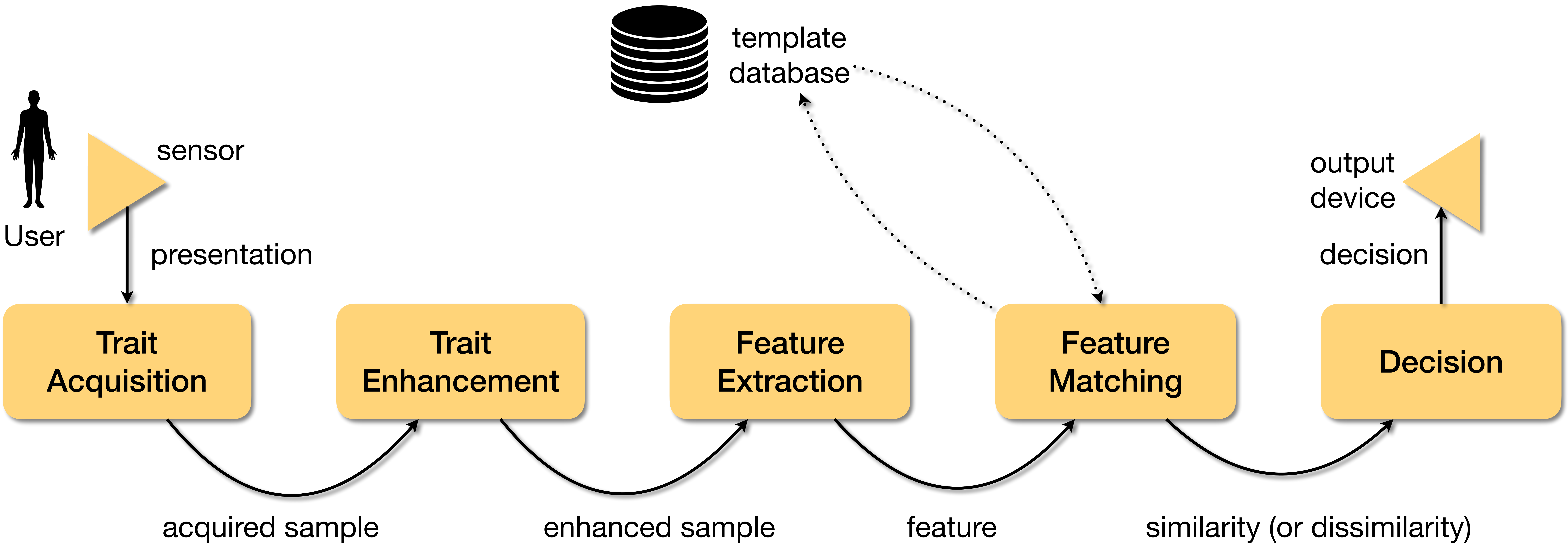
visible light

NIR

thermal

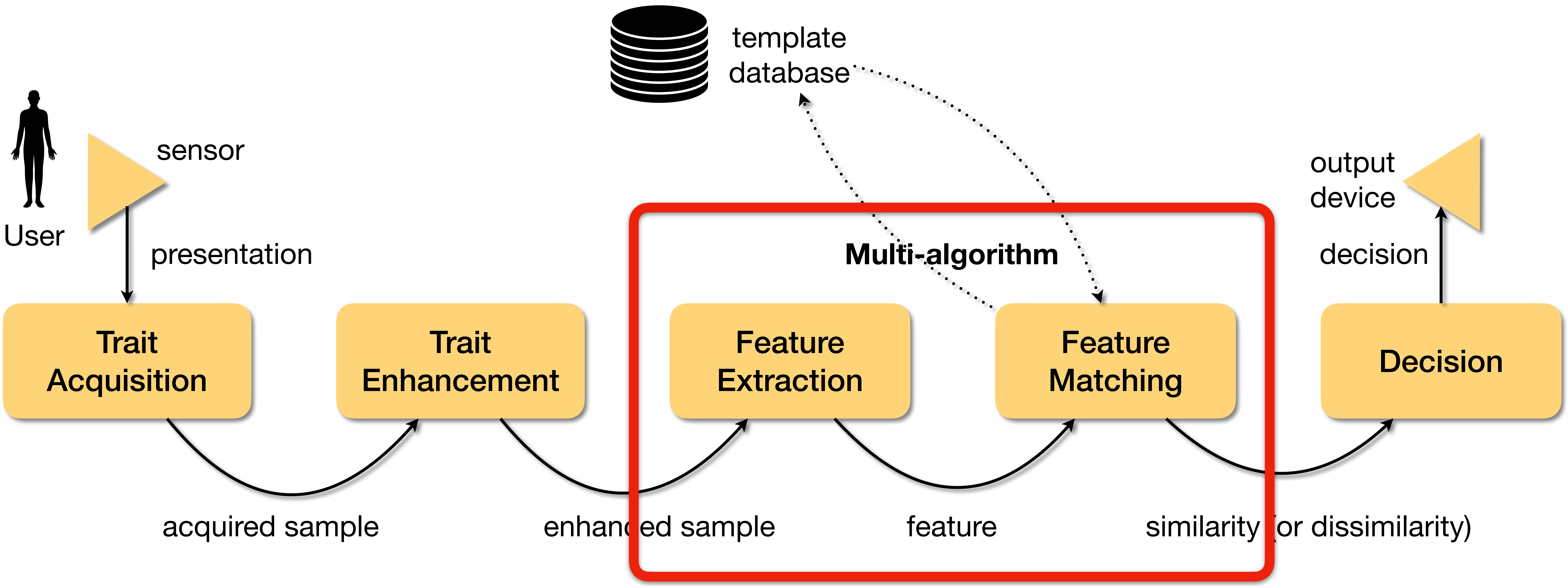
Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems

Multi-algorithm Systems (2/5)
Single trait, single sensor, multiple feature extractors and matching solutions.

Complementary solutions will lead to higher accuracy in the end.

Daugman's iris code from 2D Gabor filters

Binary code from BSIF filters.

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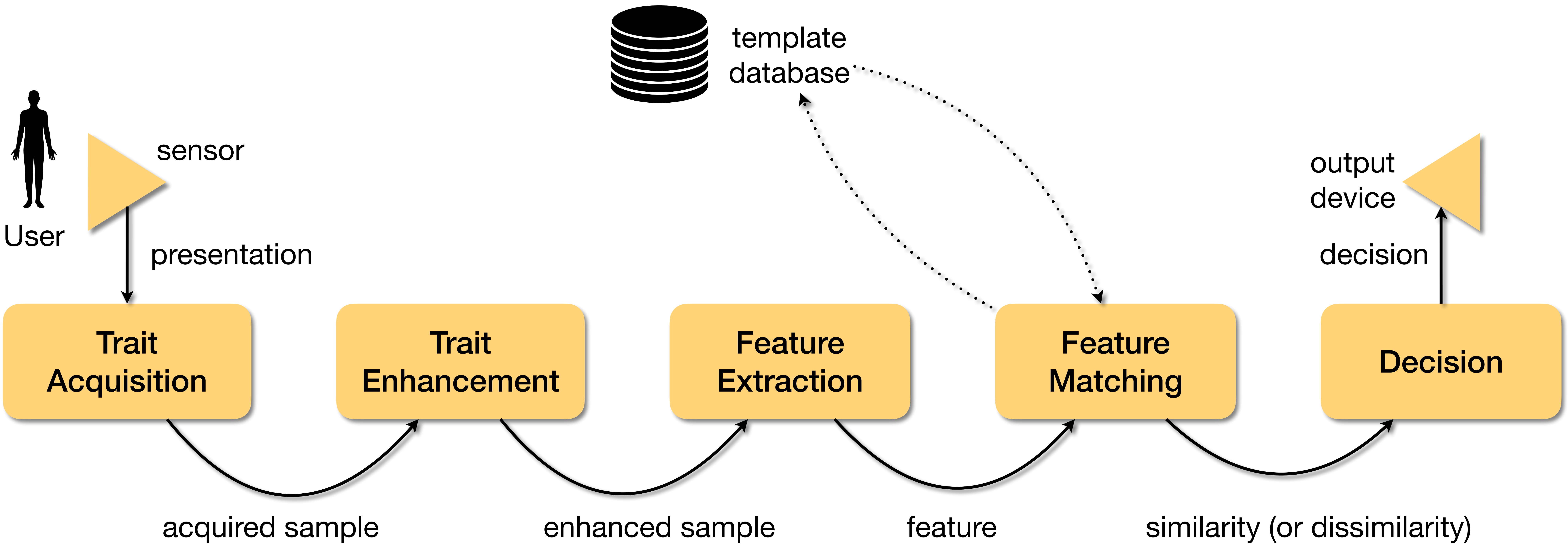
Multibiometrics

Types of Multibiometric Systems



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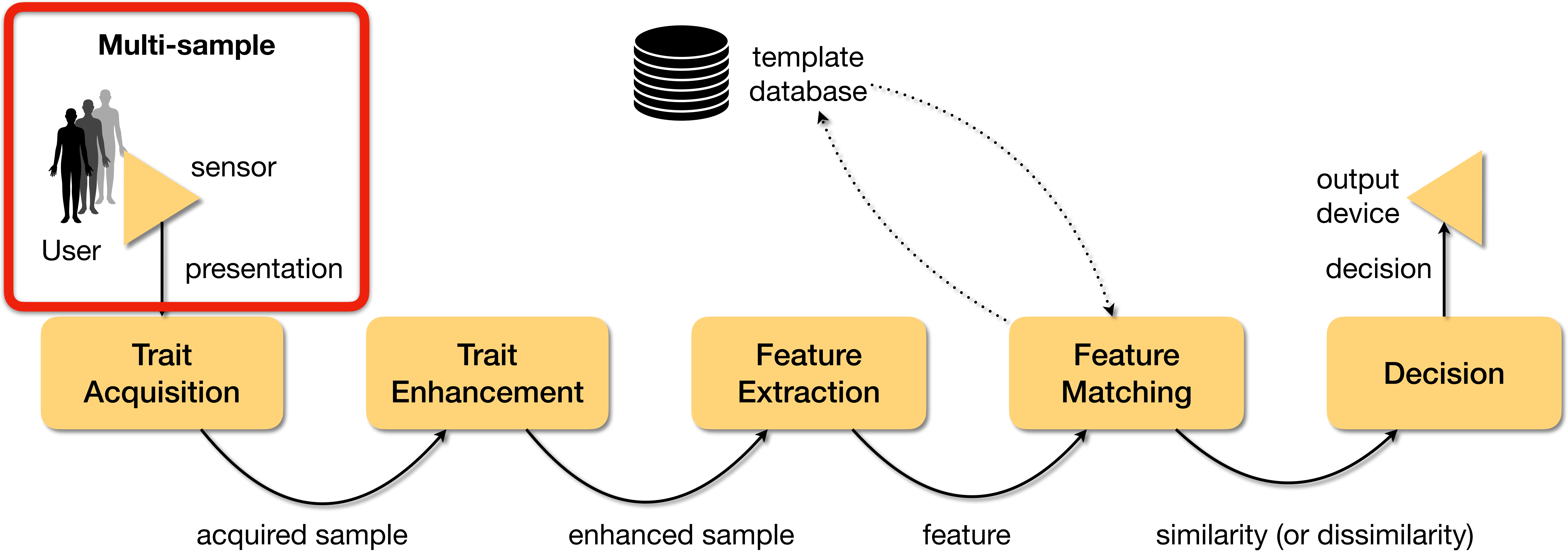
Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems

Multi-sample Systems (3/5)
Single trait, single sensor,
multiple presentations.

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More complete representation
of the trait (account for variations).

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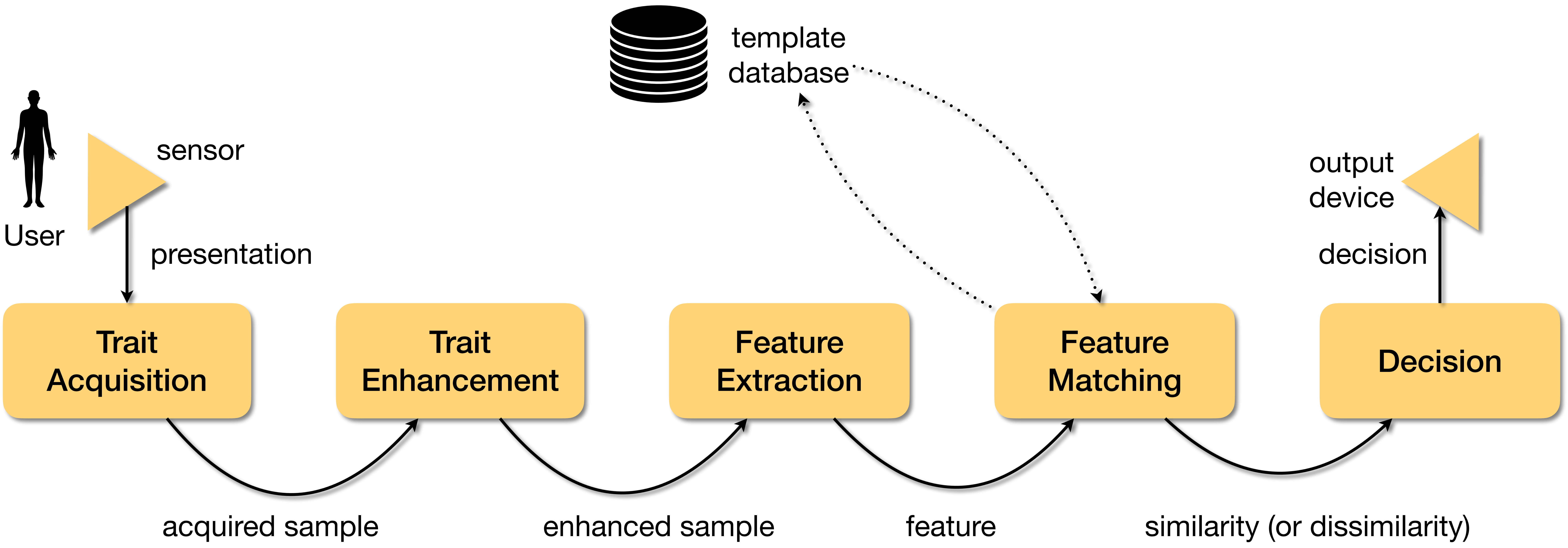
Multibiometrics

Types of Multibiometric Systems



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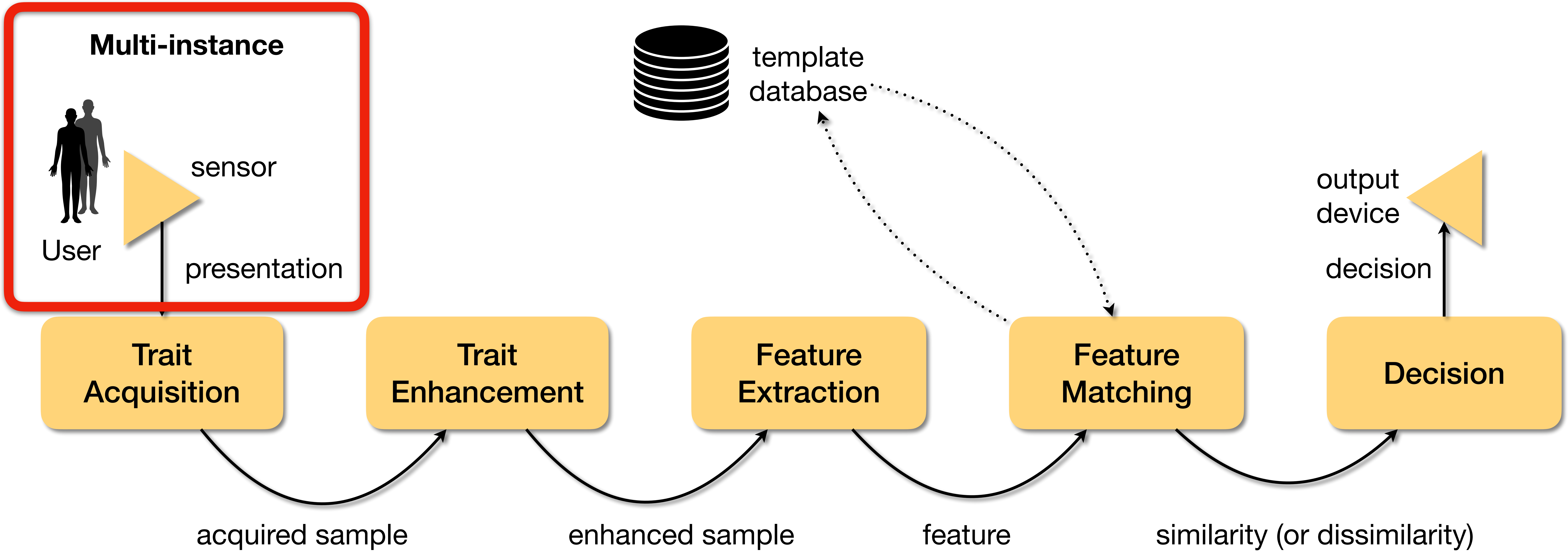
Multibiometrics

Types of Multibiometric Systems



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Multibiometrics

Types of Multibiometric Systems

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Multi-instance Systems (4/5)
Single trait, single sensor,
multiple instances
(e.g., right and left irises,
or each one of the 10 hand fingerprints, etc.).

No need for extra sensors or extra software.
Successful presentations might overcome
the failed ones.

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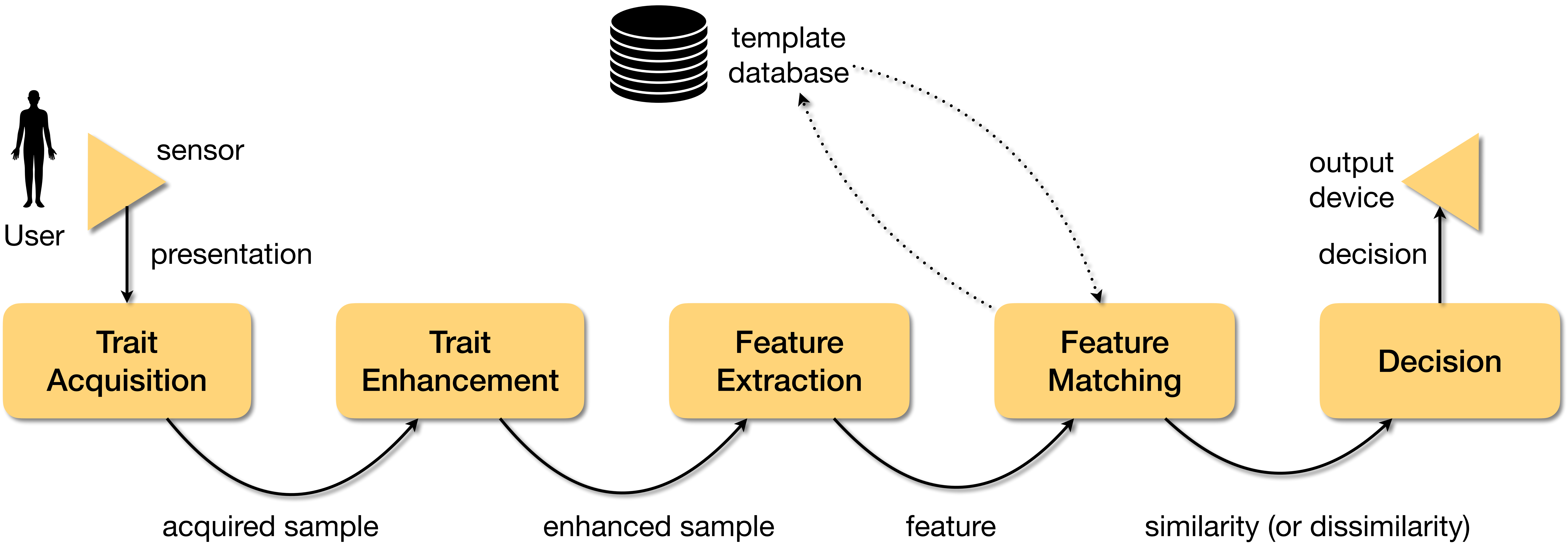
Multibiometrics

Types of Multibiometric Systems



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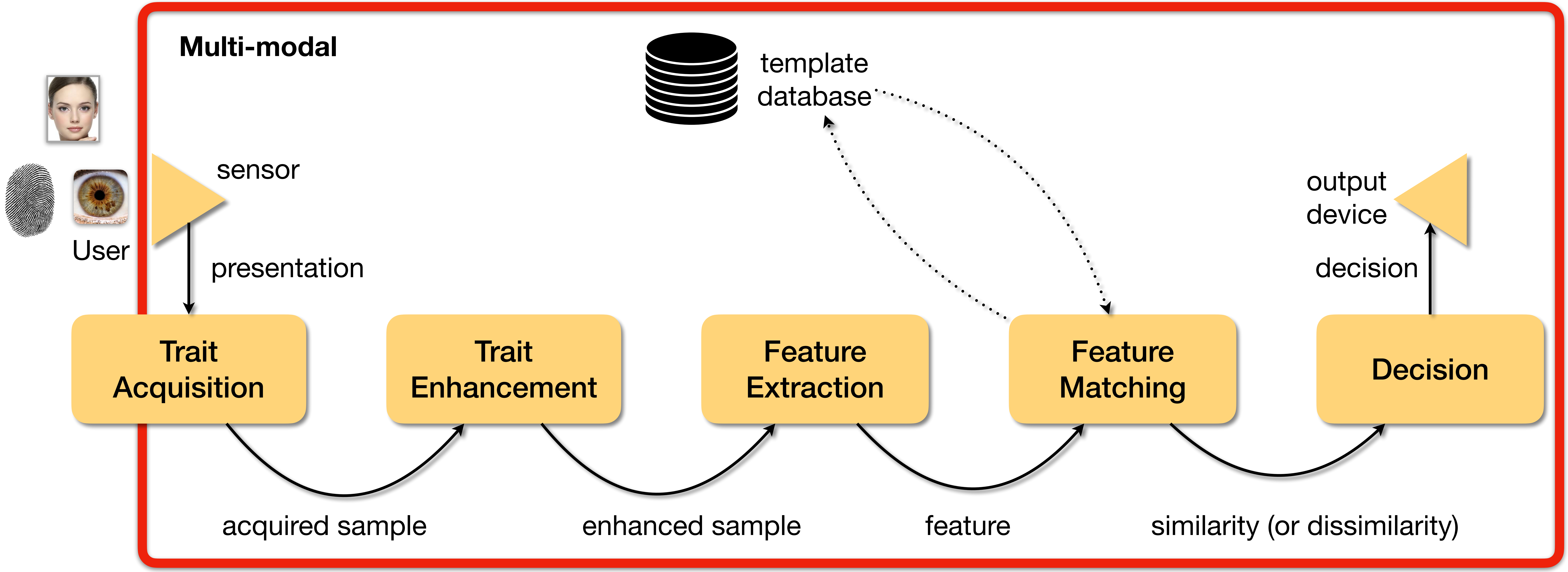
Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems

Multi-modal Systems (5/5)
Multiple traits (modalities).

Complementary solutions will lead to higher accuracy in the end.

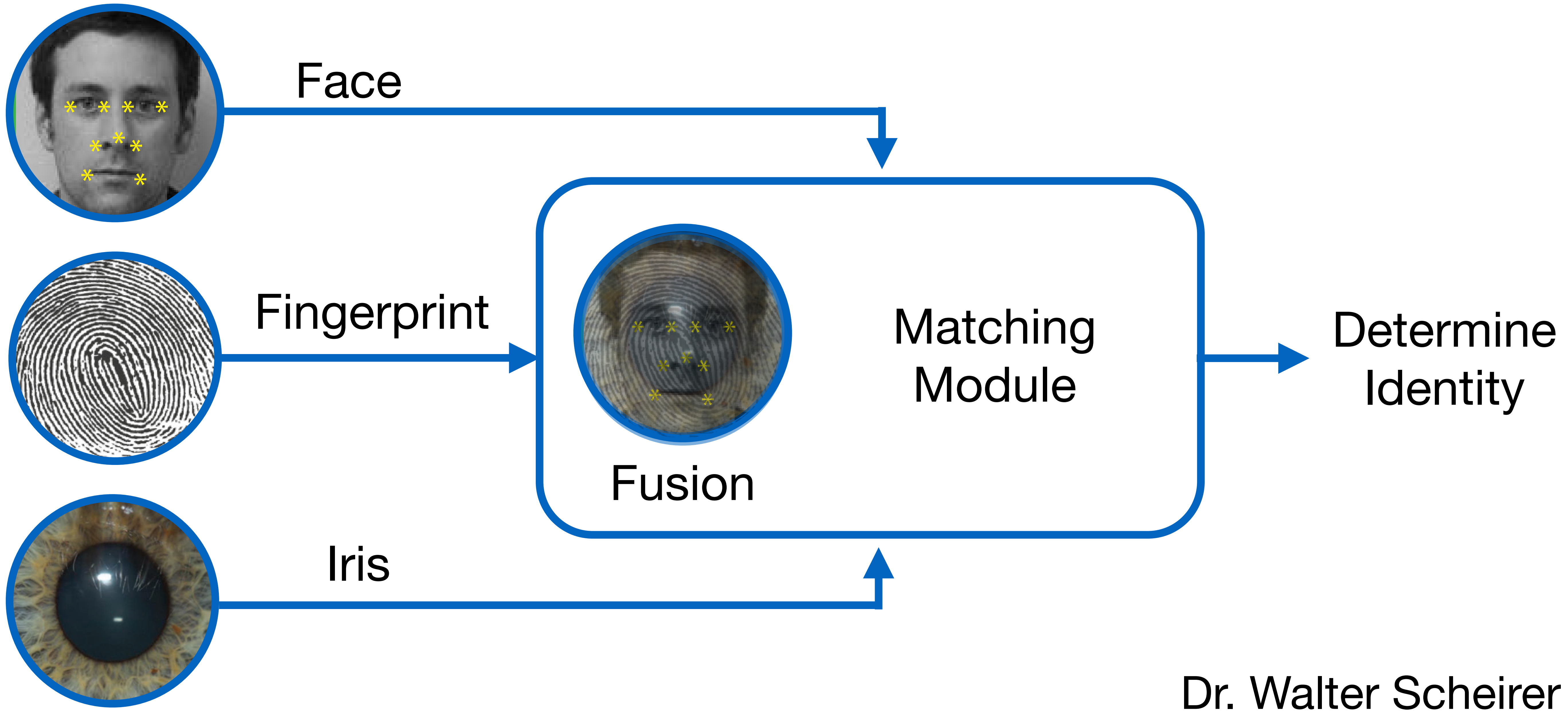
How to combine solutions?

Perform data **fusion!**

Multibiometrics

Architectures

Parallel (1/2)
Evidence acquired from multiple sources is processed simultaneously.



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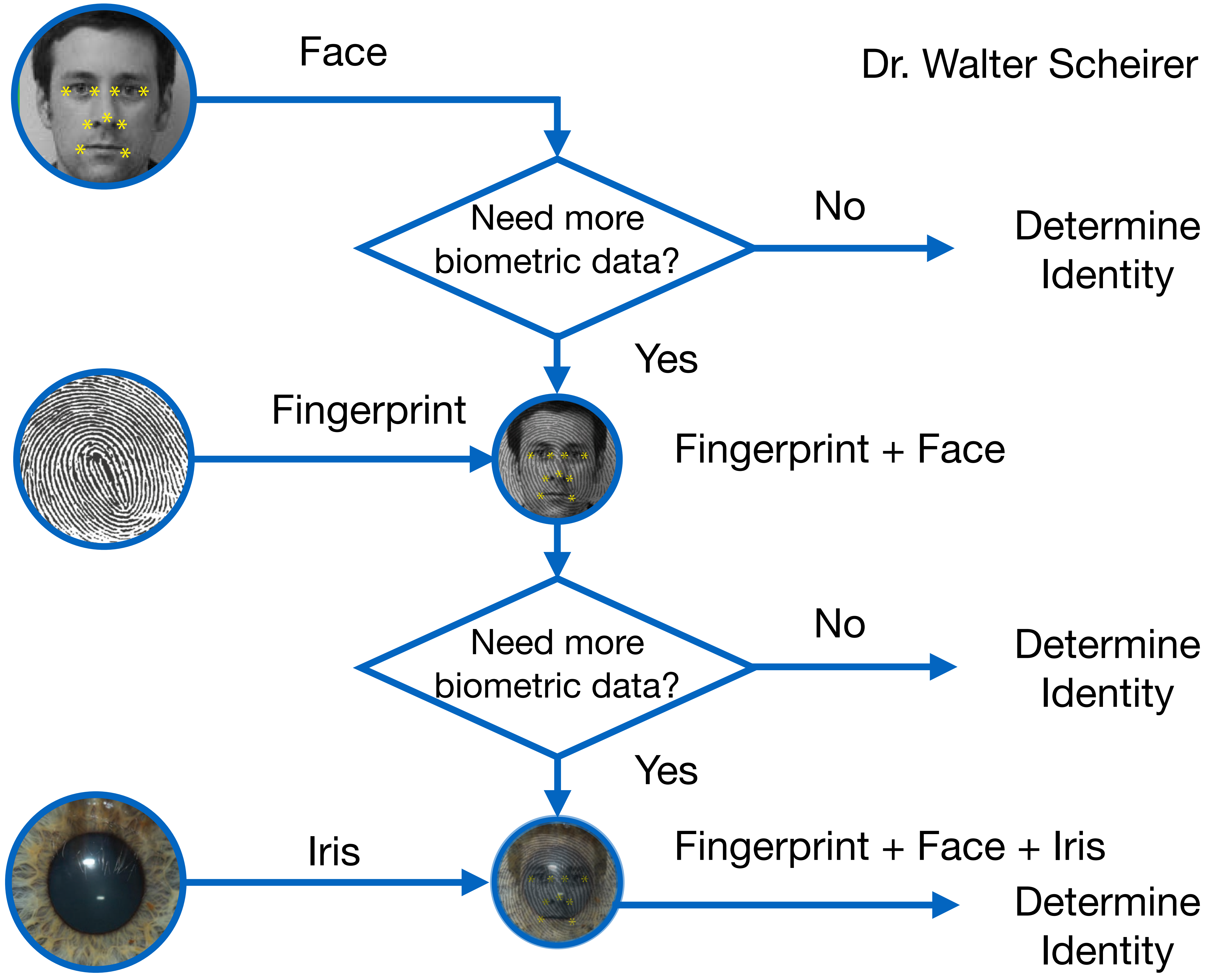
Multibiometrics

Architectures

Cascade (2/2)
Multiple sources are processed on demand (e.g., whenever a decision score is not confident enough).



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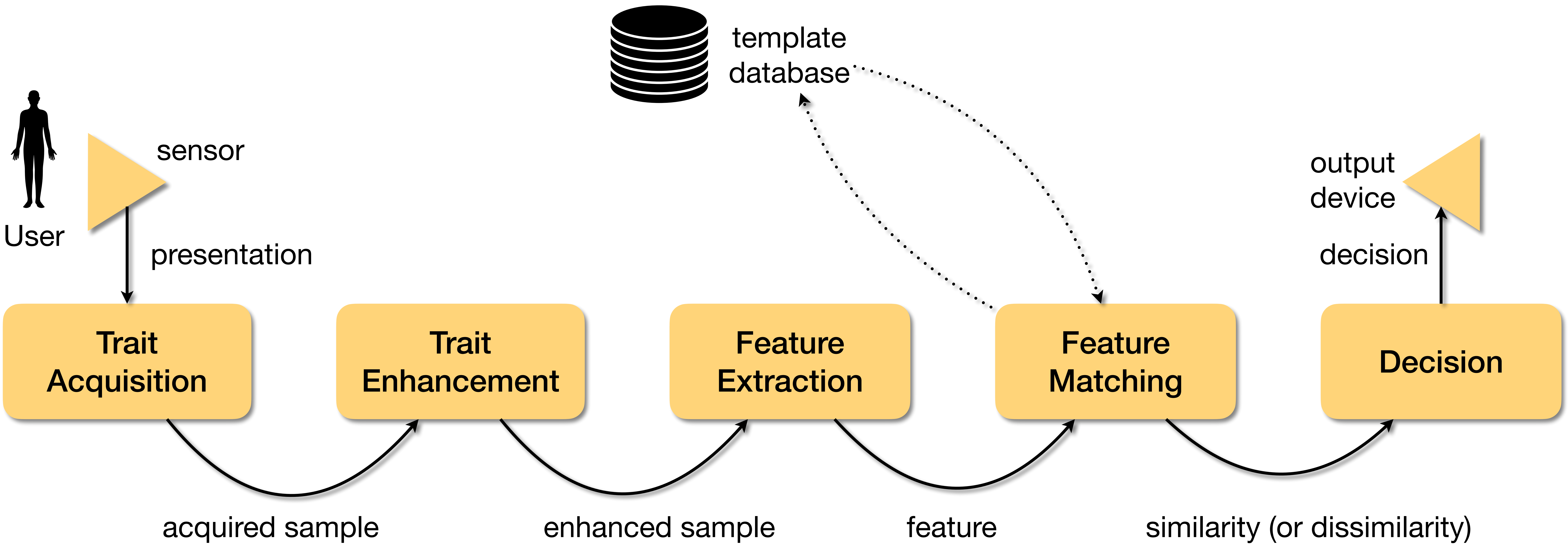
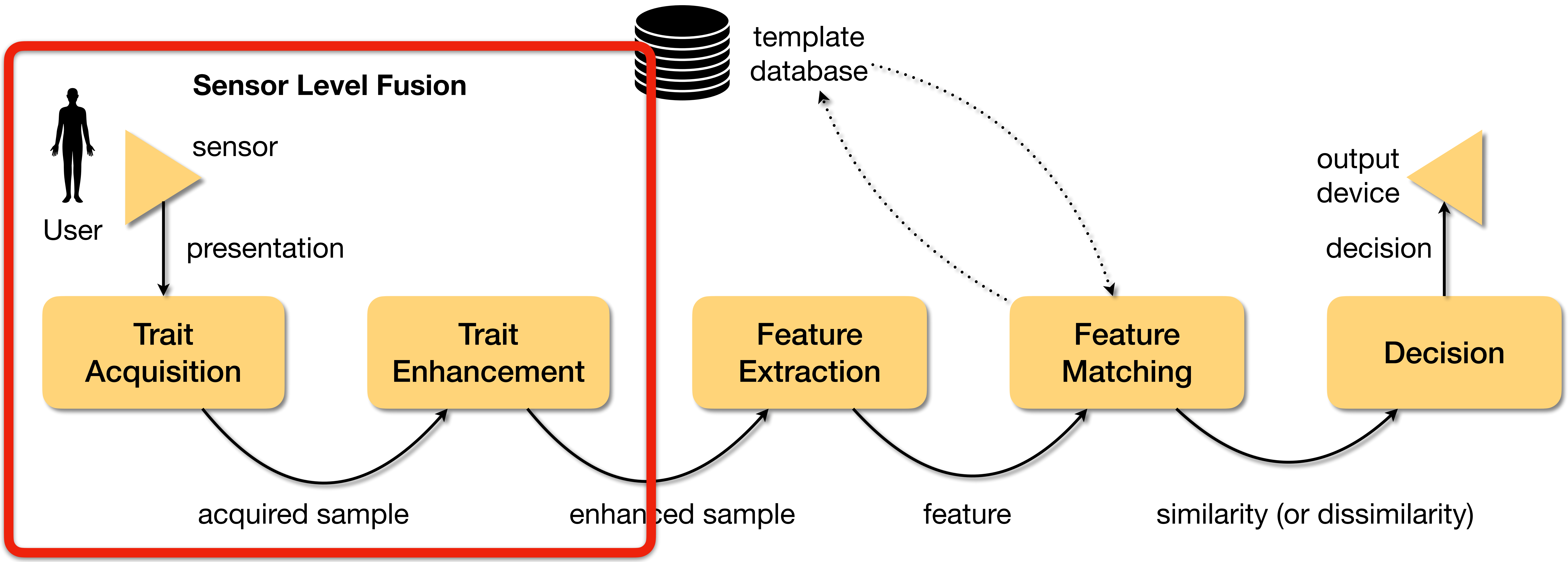
Multibiometrics

Data Fusion Levels



Multibiometrics

Data Fusion Levels

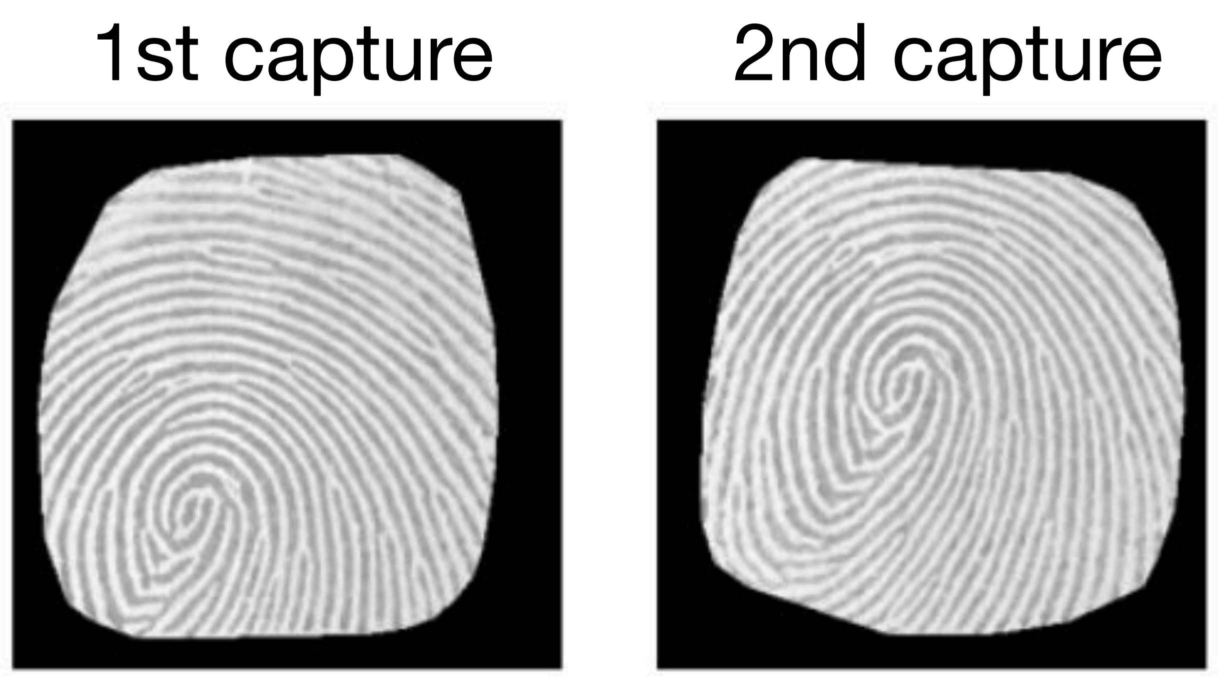


Multibiometrics

Data Fusion Levels

Sensor Level Fusion
Multiple sources of raw data are consolidated before feature extraction.

Example
Different captures of the same fingerprint are combined to generate sample larger than sensor capacity.



Multibiometrics

Data Fusion Levels

Sensor Level Fusion
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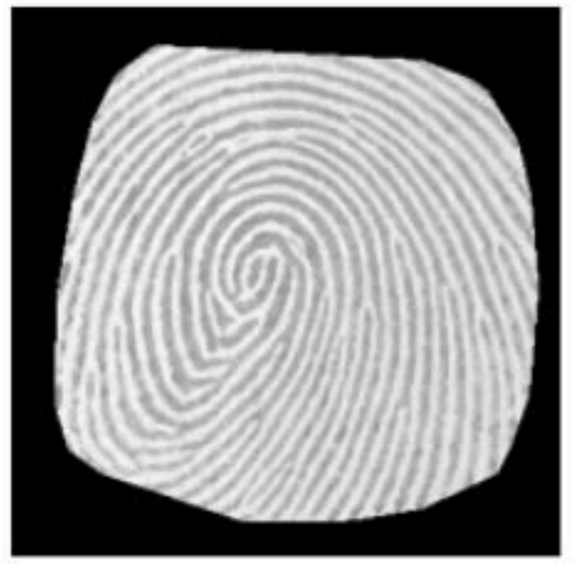
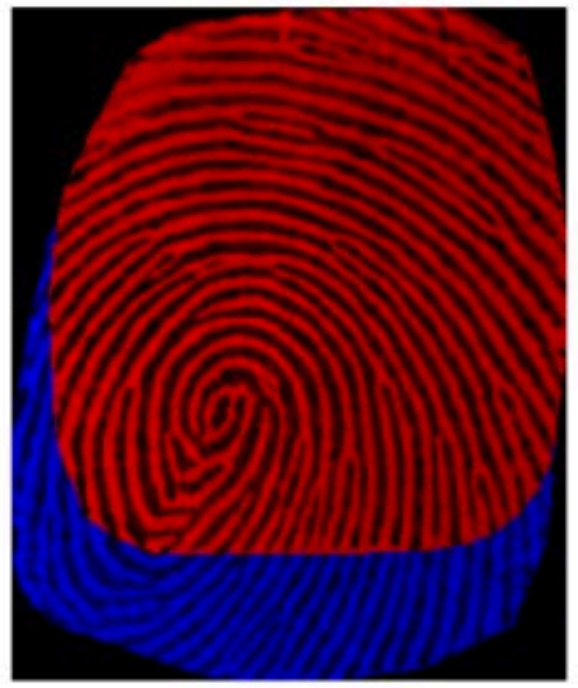
Example
Different captures of the same fingerprint are combined to generate sample larger than sensor capacity.

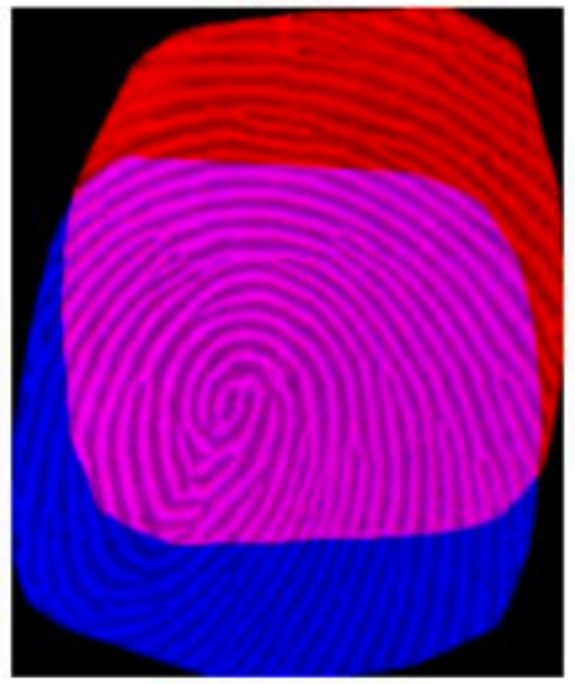
1st capture

2nd capture



initial alignment





final alignment

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Multibiometrics

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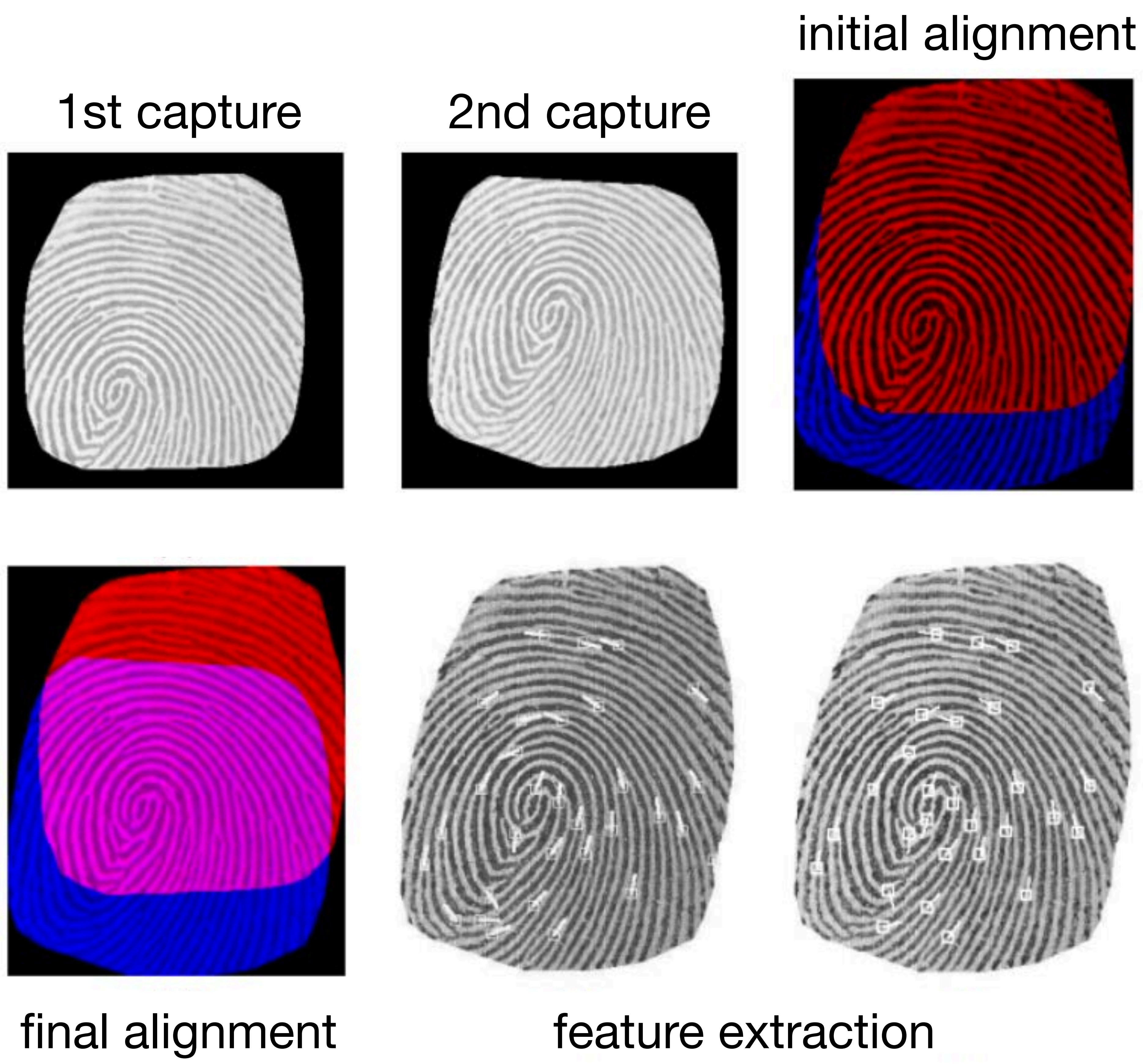
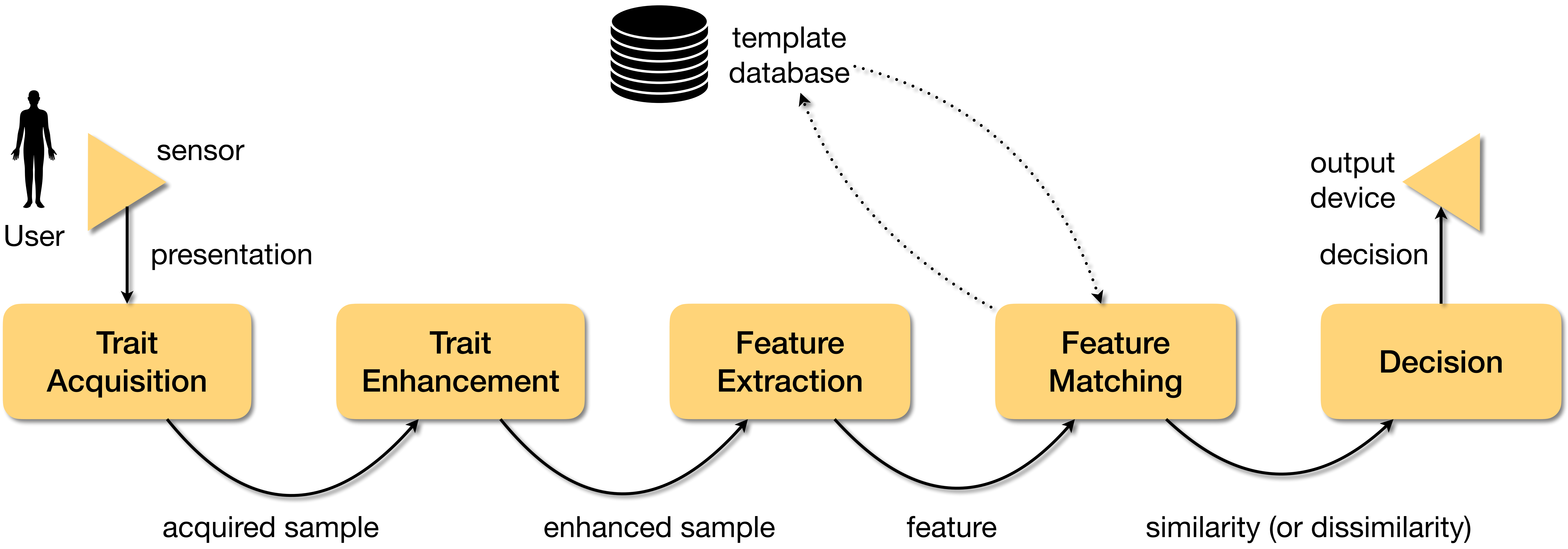


Jain and Ross
Fingerprint Mosaicking
ICASSP 2002

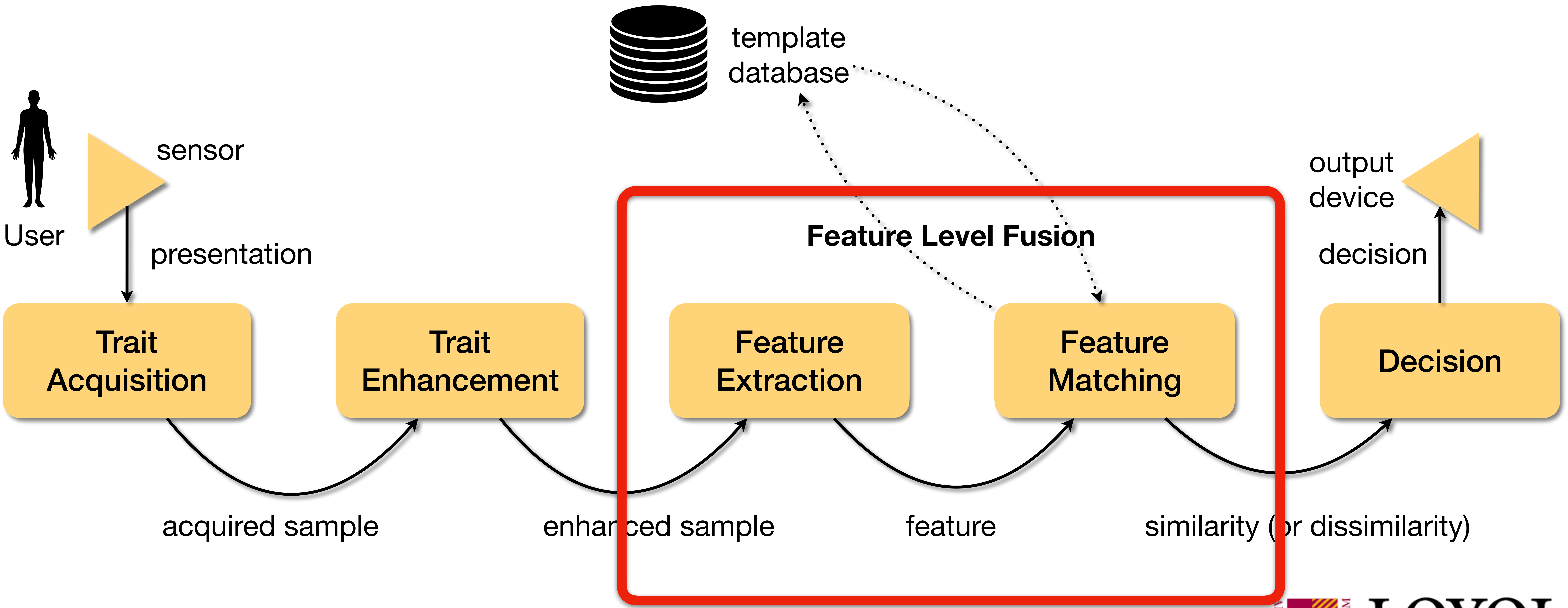
Multibiometrics

Data Fusion Levels



Multibiometrics

Data Fusion Levels

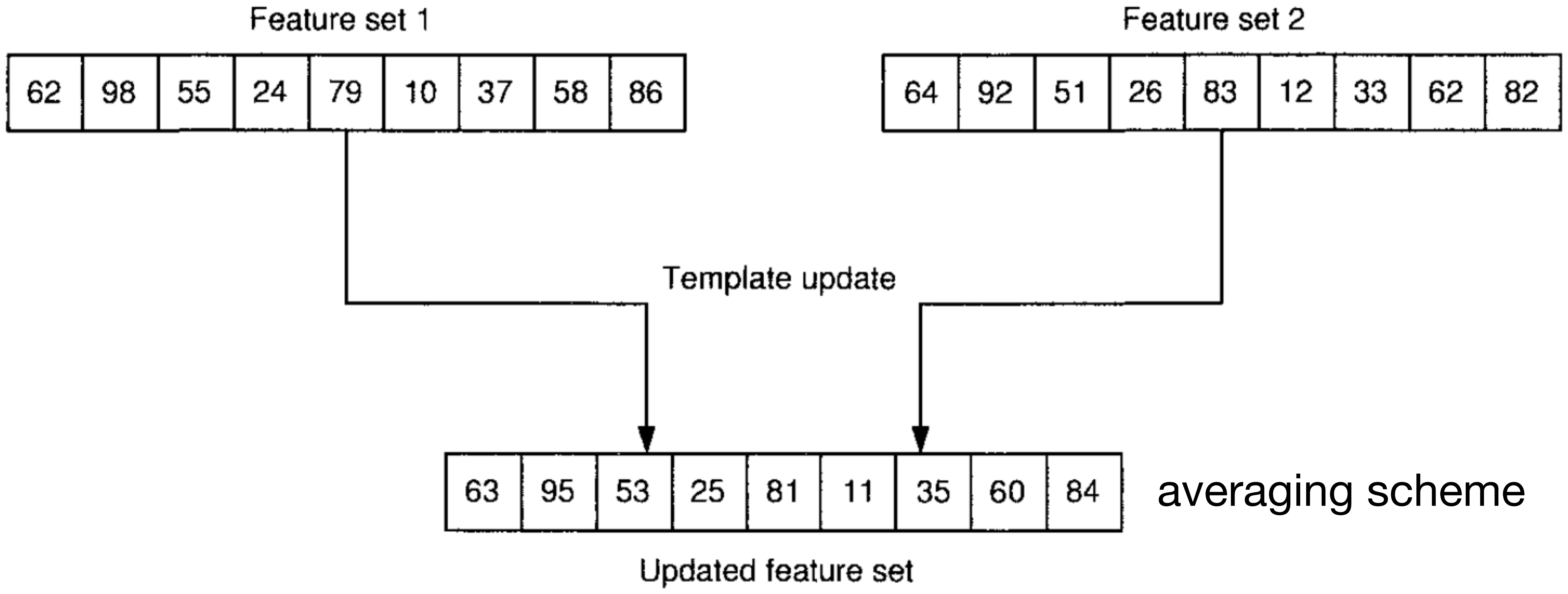


Multibiometrics

Ross, Nandakumar, and Jain
Handbook of Multibiometrics
Springer Books, 2006

Data Fusion Levels

Feature Level Fusion
Multiple feature vectors from the same individual are combined into a single feature vector, prior to matching.



averaging scheme

Example Strategies
Linear combination, concatenation, etc.

Multibiometrics

Data Fusion Levels

Feature Level Fusion
Challenges

Multi-sensor Systems	Different-nature feature vectors.
Multi-algorithm Systems	Different-nature feature vectors.
Multi-sample Systems	Same-nature feature vectors.
Multi-instance Systems	Same-nature feature vectors.
Multi-modal Systems	Different-nature feature vectors.

Multibiometrics

Data Fusion Levels

Feature Level Fusion
Challenges

Multi-sensor Systems	**Different-nature feature vectors.**
Multi-algorithm Systems	**Different-nature feature vectors.**
Multi-sample Systems	Same-nature feature vectors.
Multi-instance Systems	Same-nature feature vectors.
Multi-modal Systems	**Different-nature feature vectors.**

Multibiometrics

Data Fusion Levels

Feature Level Fusion
Challenges

How to combine features of different nature?
(e.g., different domains, different scales, different ranges of values, etc.).

Typical solutions: **concatenation, normalization.**
Caution: too-large vectors will suffer from the **curse of dimensionality**.

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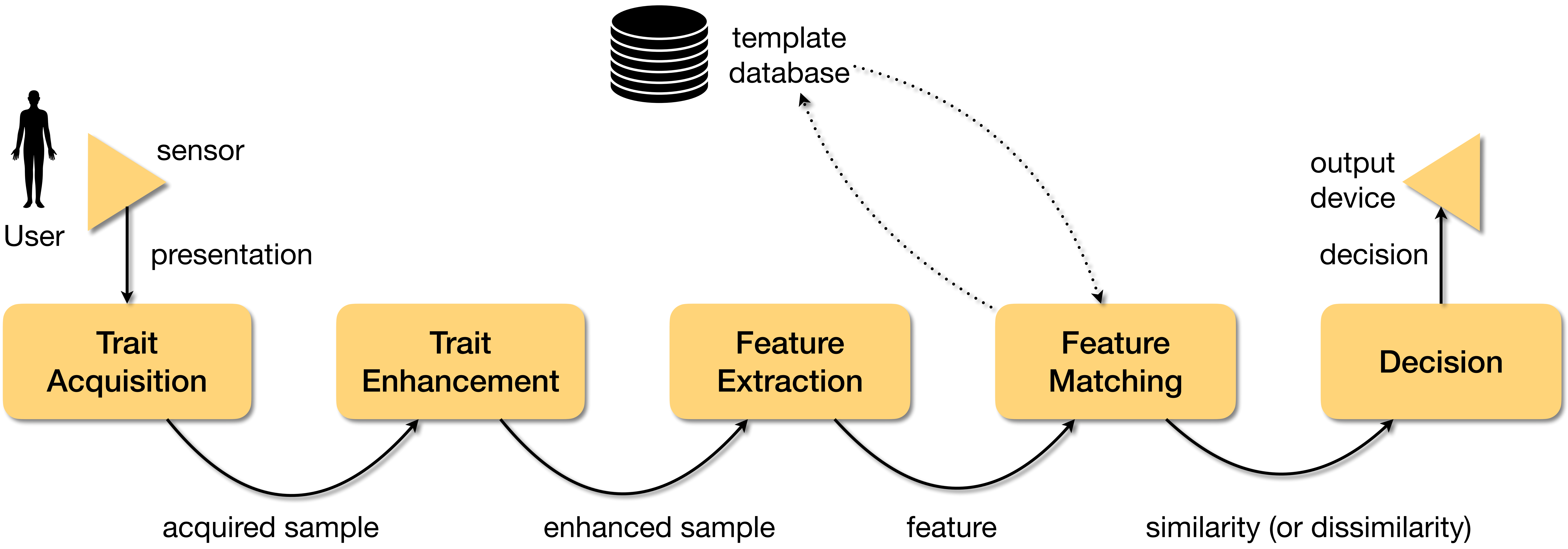
Multibiometrics

Data Fusion Levels



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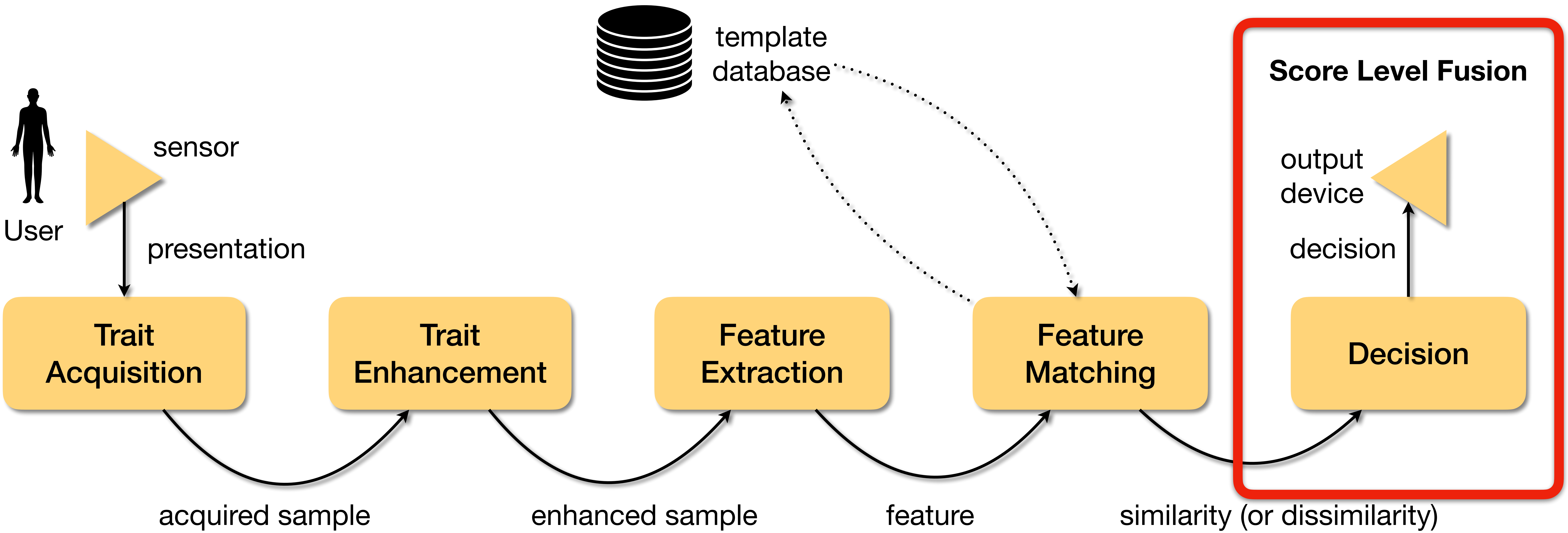
Multibiometrics

Data Fusion Levels



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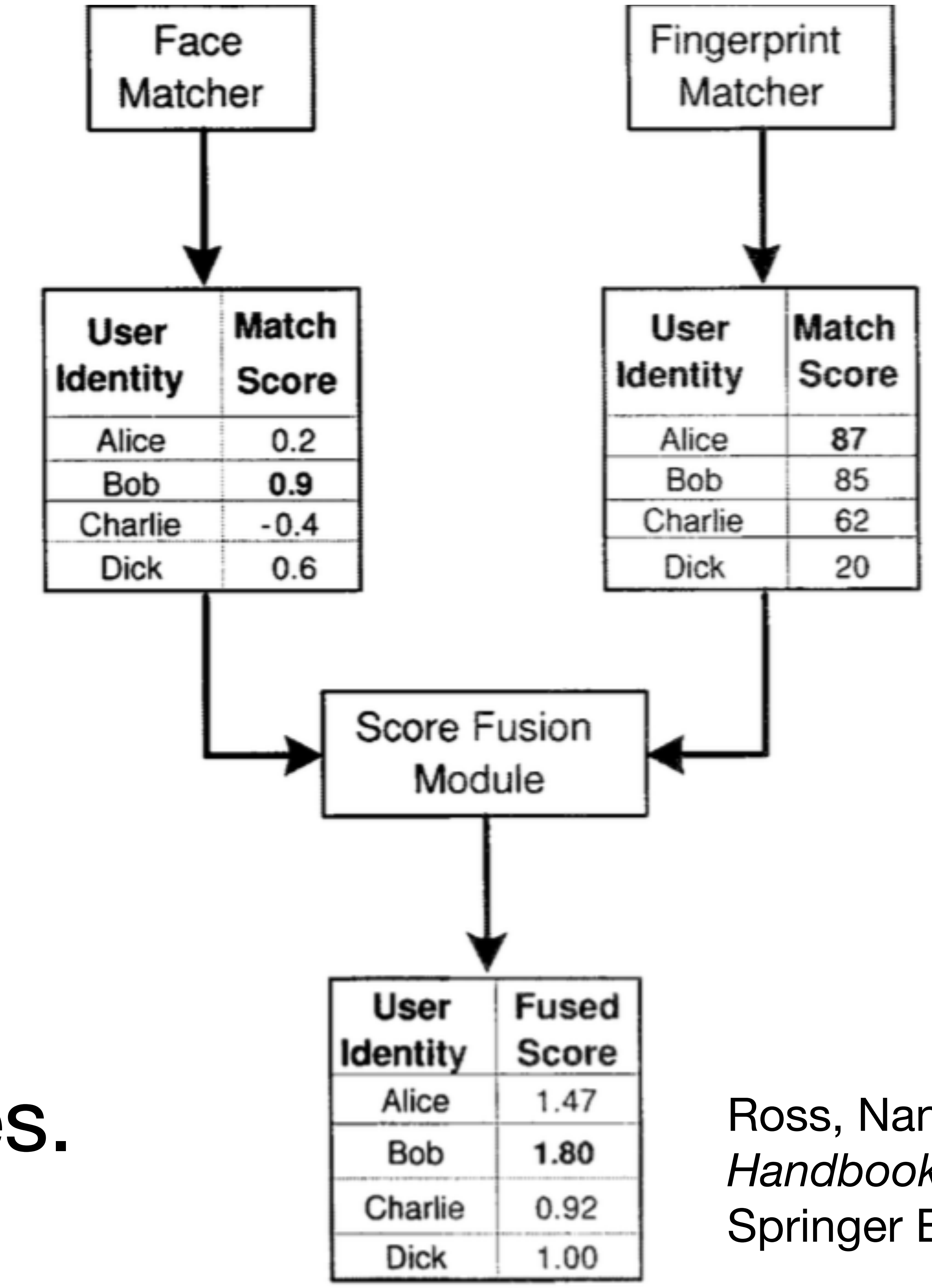
Data Fusion Levels

Score Level Fusion
Scores (similarities or dissimilarities) from different matching algorithms are consolidated before final decision.

Strategies
Discriminative versus *generative* approaches.



Ross, Nandakumar, and Jain
Handbook of Multibiometrics
Springer Books, 2006

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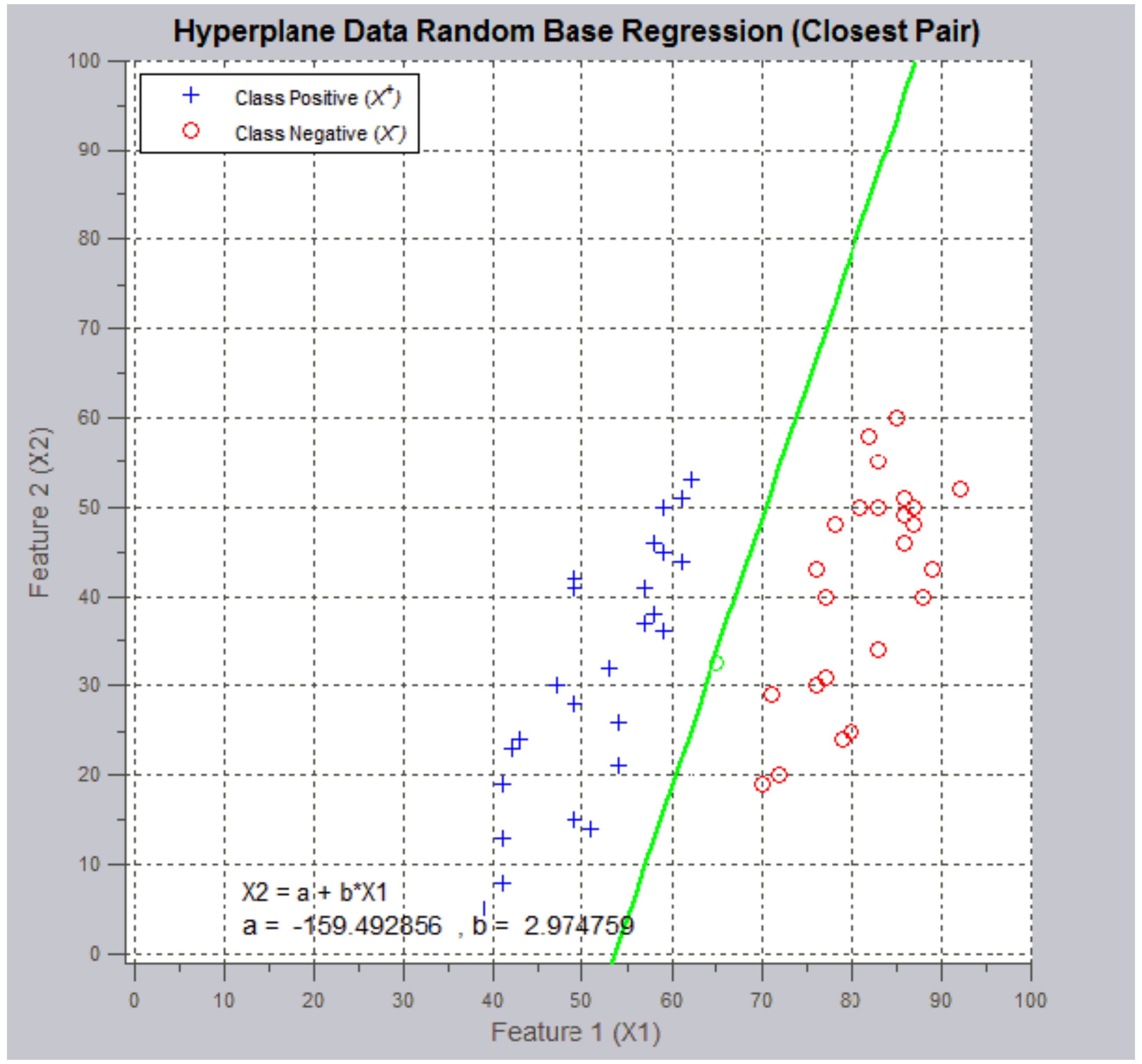
Multibiometrics

Data Fusion Levels

Score Level Fusion
Discriminative Approaches

Thresholds, separation hyperplanes, decision trees, etc. are used to decide the Biometric system outcome (impostor versus genuine).



Example: Support Vector Machine (SVM)

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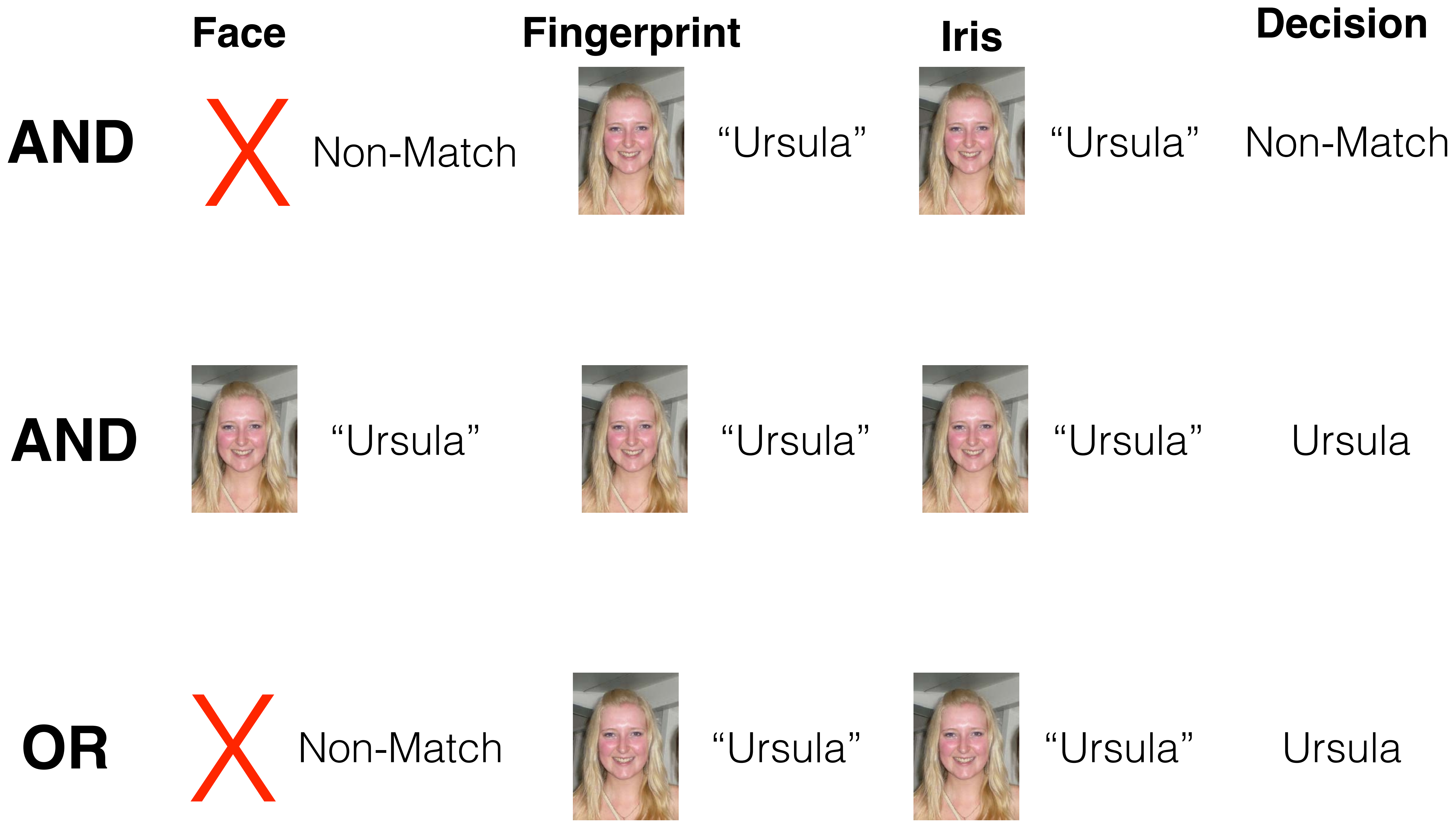
Multibiometrics

Data Fusion Levels

Score Level Fusion
Discriminative Approaches

Examples:
AND and OR rules.



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Multibiometrics

Data Fusion Levels

Score Level Fusion
Discriminative Approaches

Examples:
Majority Voting.

Face		**Fingerprint**		**Iris**		**Decision**
	“Gudrun”		“Ursula”		“Ursula”	$votes = 2$ Ursula

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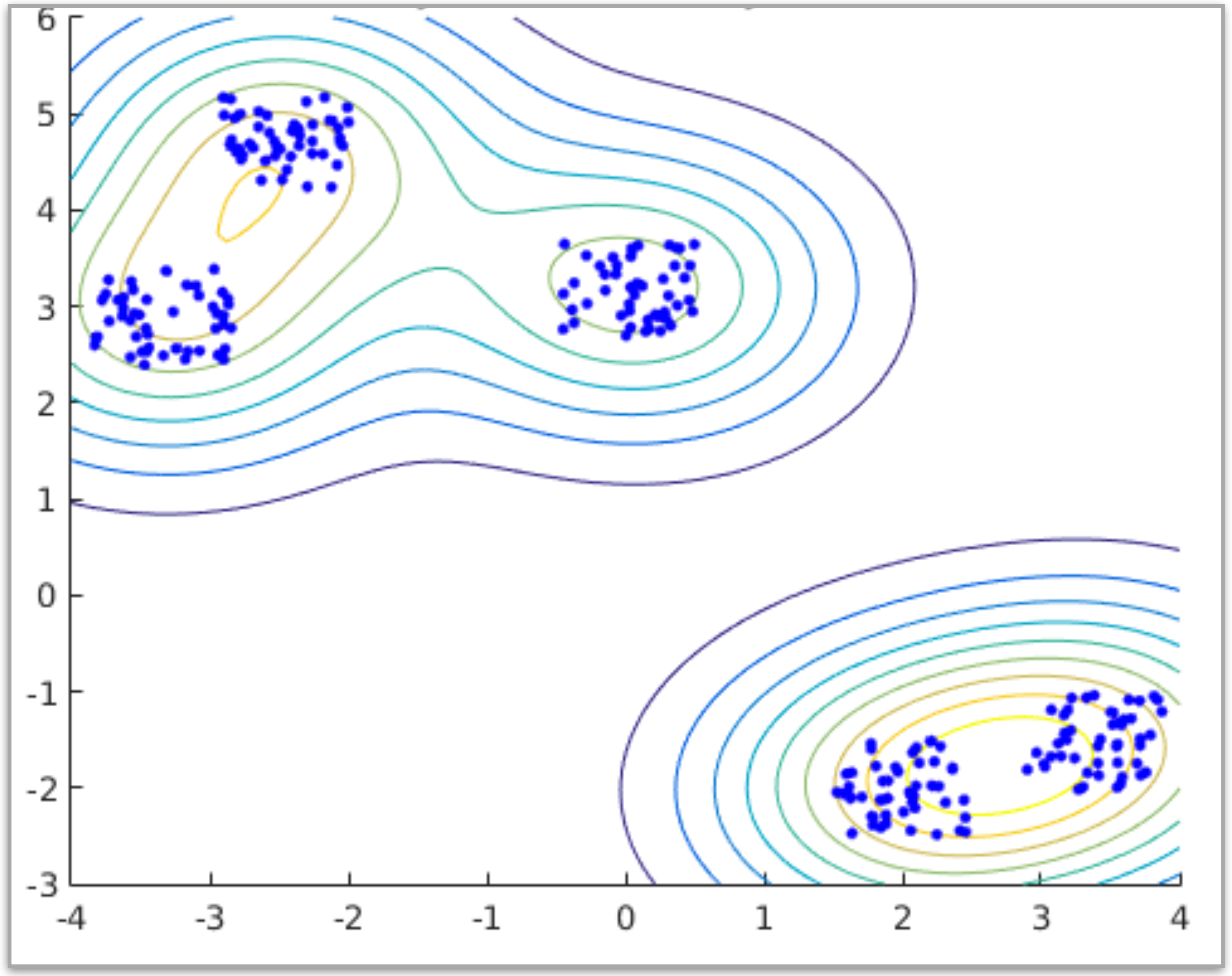
Multibiometrics

Data Fusion Levels

Score Level Fusion
Generative Approaches



Data distribution models of the joint probability of observations and scores are computed in *training* time and further used in *operation* time to return the probability of a presentation be either impostor or genuine.

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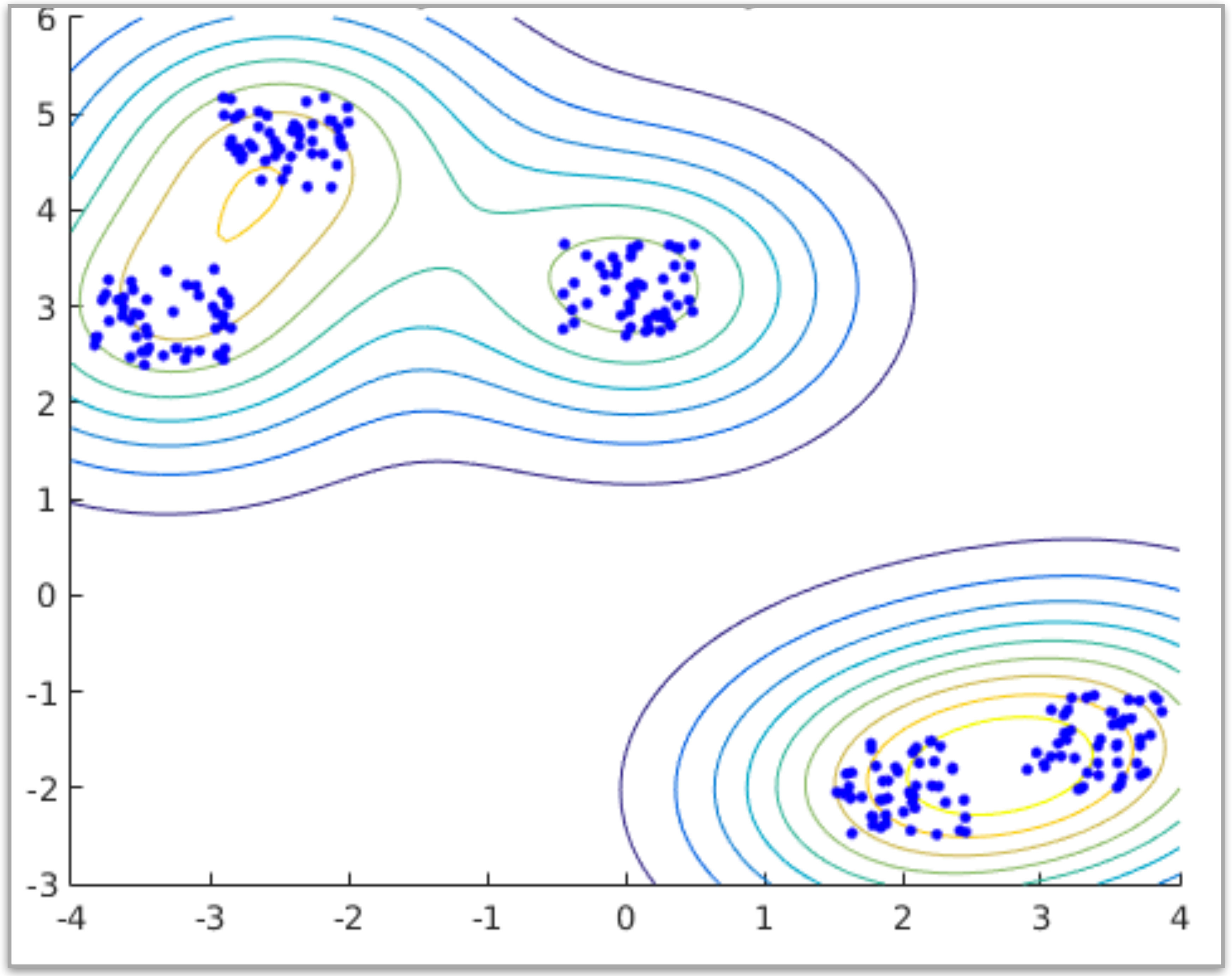
Data Fusion Levels

Score Level Fusion
Generative Approaches

Examples: Naïve Bayes,
Gaussian Mixture Models (GMM),
Extreme-Value Theory, etc.



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Multibiometrics

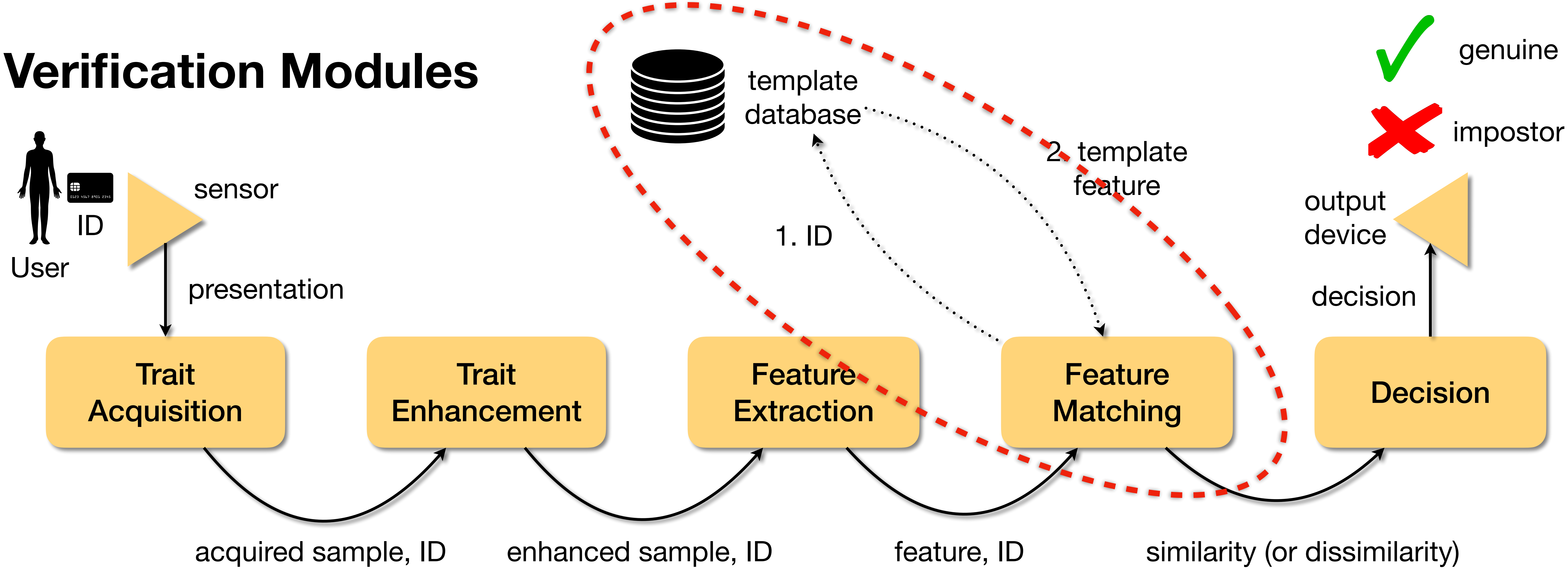
Data Fusion Levels

Score Level Fusion
Pros

Regardless of being either discriminative or generative, it can be used with commercial off-the-shelf matchers that do not expose their feature vectors but return confidence scores.

What’s Next?

Verification Modules



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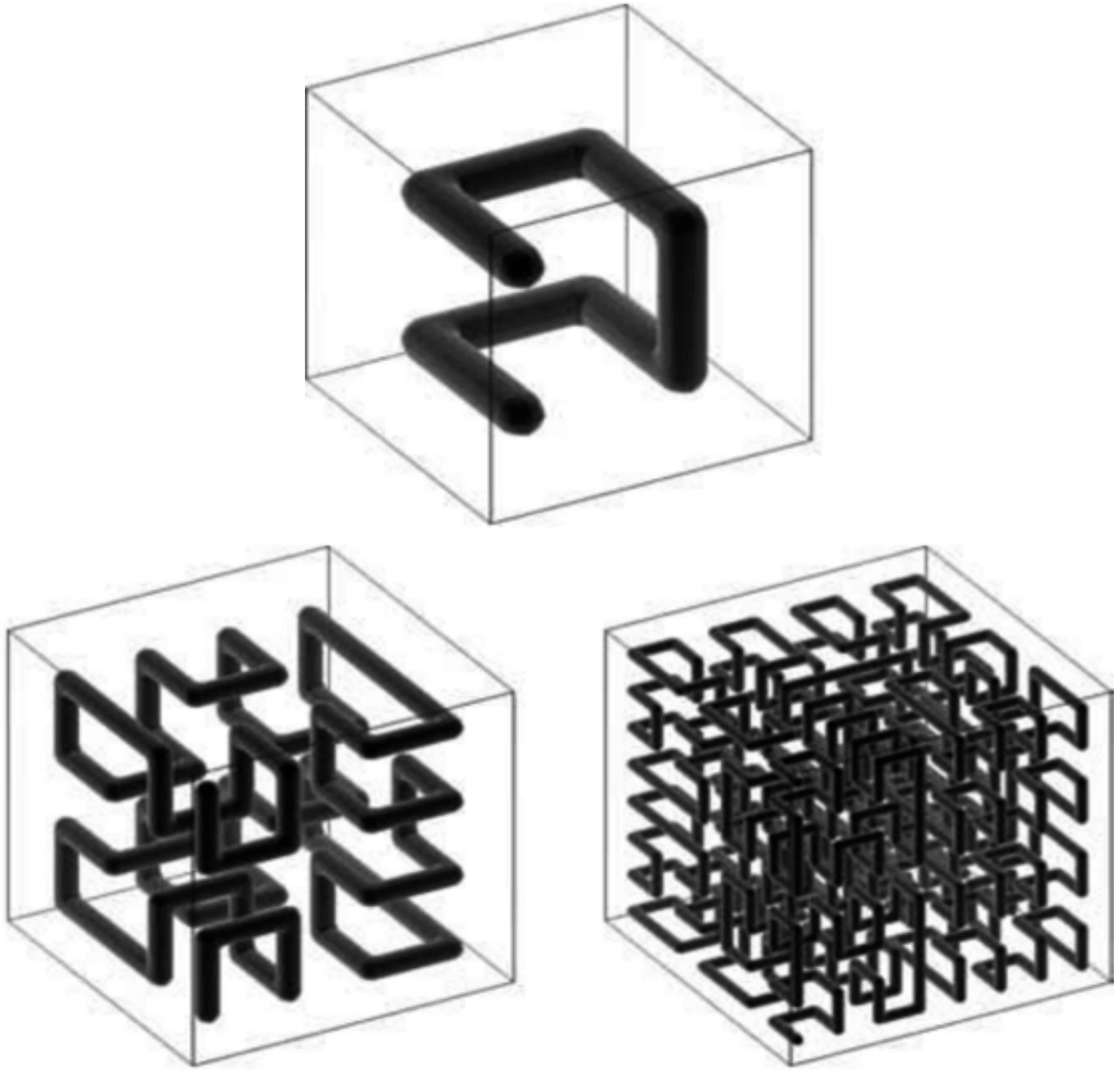
What’s Next?

Feature Indexing.

Fill out your
Today-I-missed **Statement**
Please visit
https://sakai.luc.edu/x/PnQvIG.



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