


Revisiting and Improving Scoring Fusion for Spoofing-aware Speaker Verification Using Compositional Data Analysis

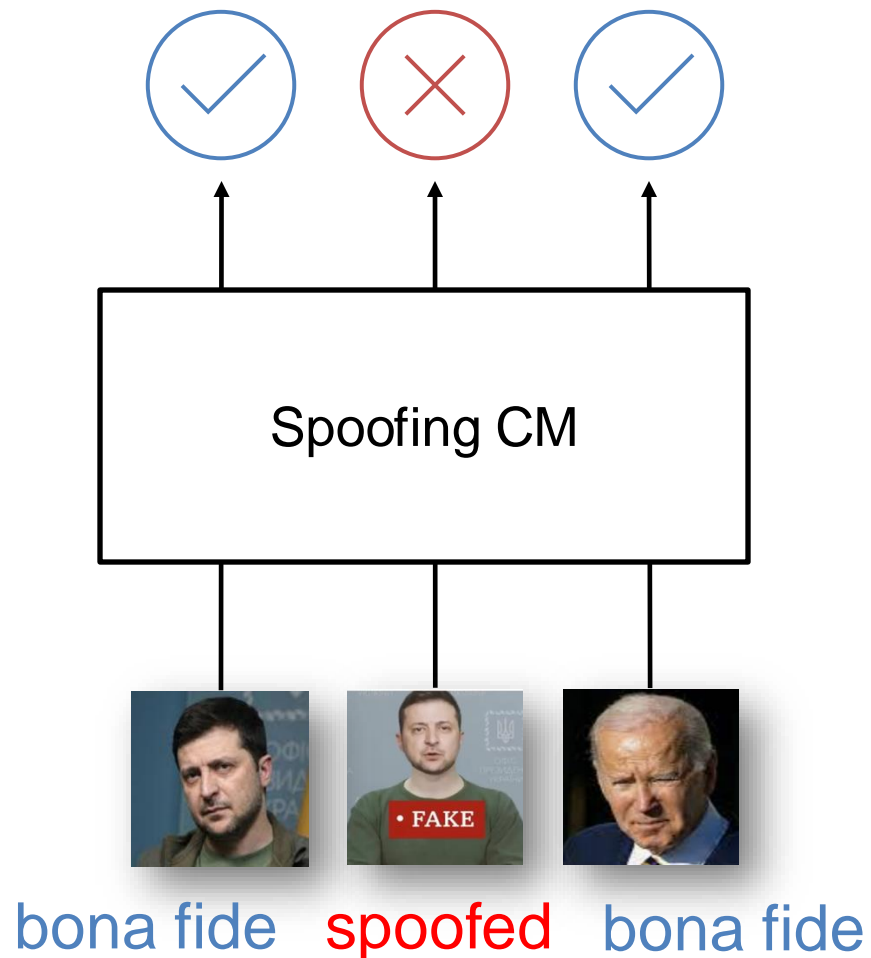
Xin Wang , Tomi Kinnunen, Kong Aik Lee,
Paul-Gauthier Noe, Junichi Yamagishi
NII, JST PRESTO, UEF, PolyU, Inria

Summary in one slide

- ❑ Question: how ASV and spoofing countermeasure (CM) should be fused **theoretically**?
- ❑ Message: fusing ASV and CM \neq fusing ASVs (or CMs)
- ❑ Methods
 - Linear fusion of log likelihood ratios (LLRs)
 - Non-linear fusion of LLRs
- ❑ Results: both better than baseline, non-linear the best

} Bayesian
decision theory

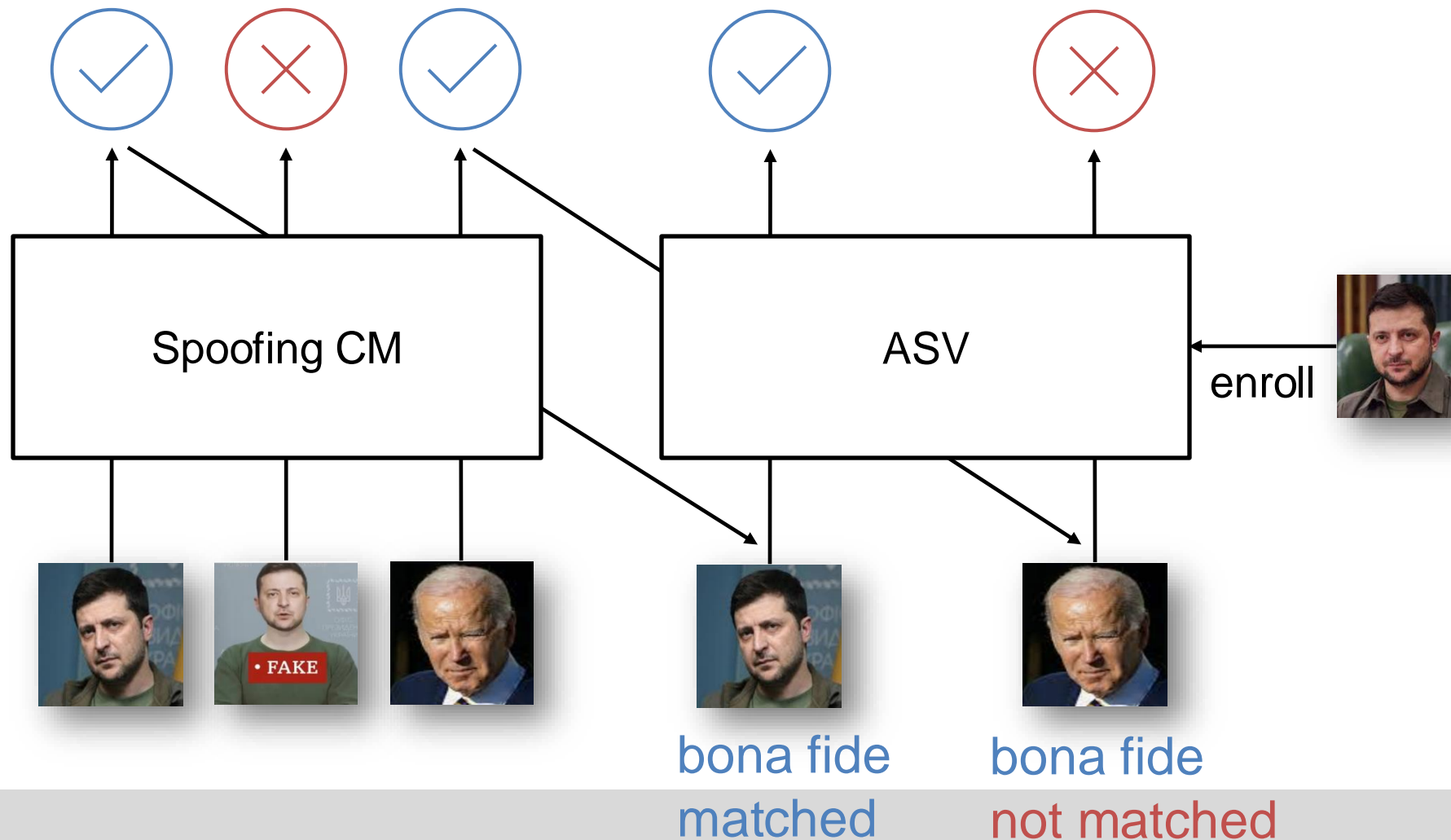
Background: spoofing CM



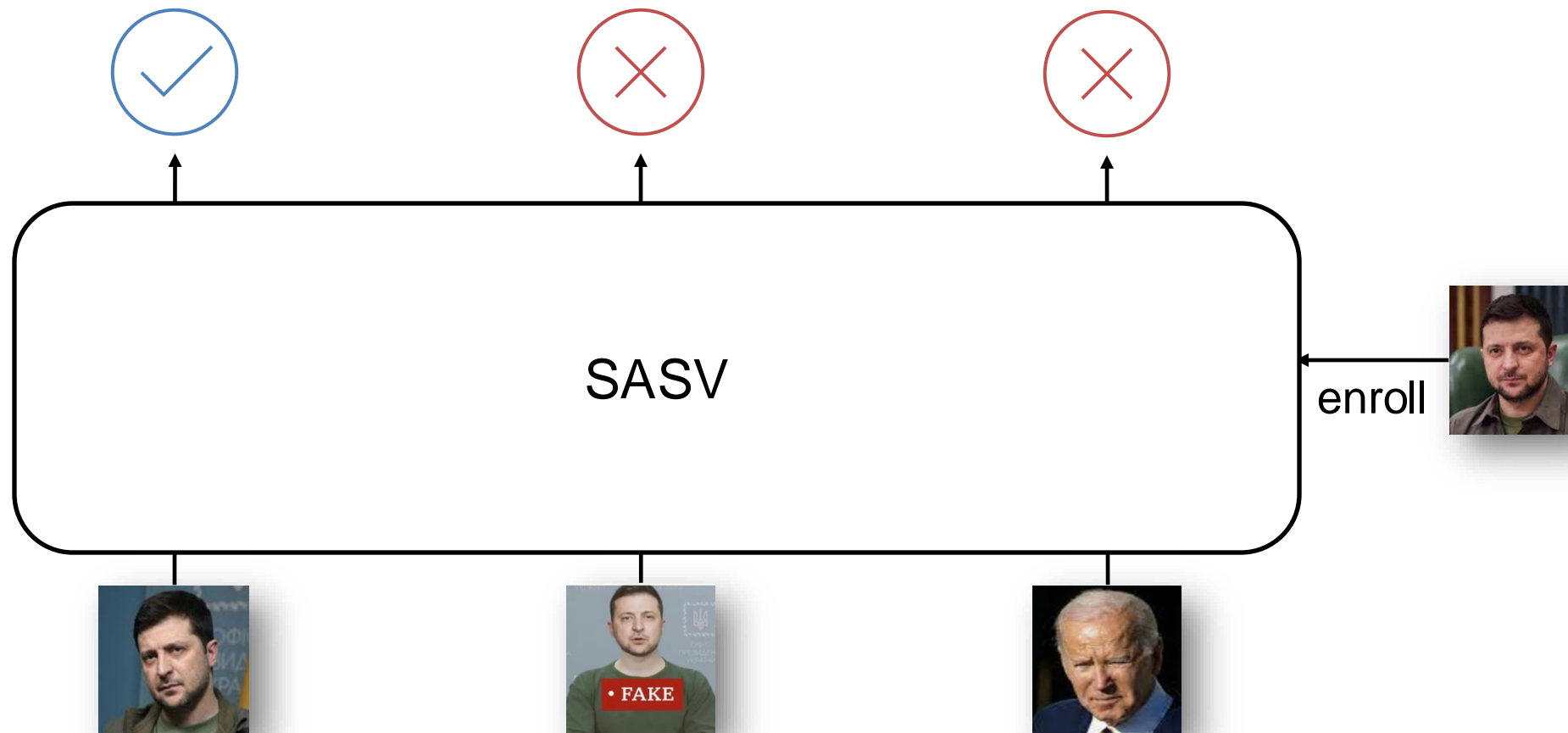
protect human listeners

protect ASV

Background: spoofing CM protecting ASV



Background: spoofing-robust ASV (SASV)

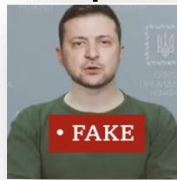
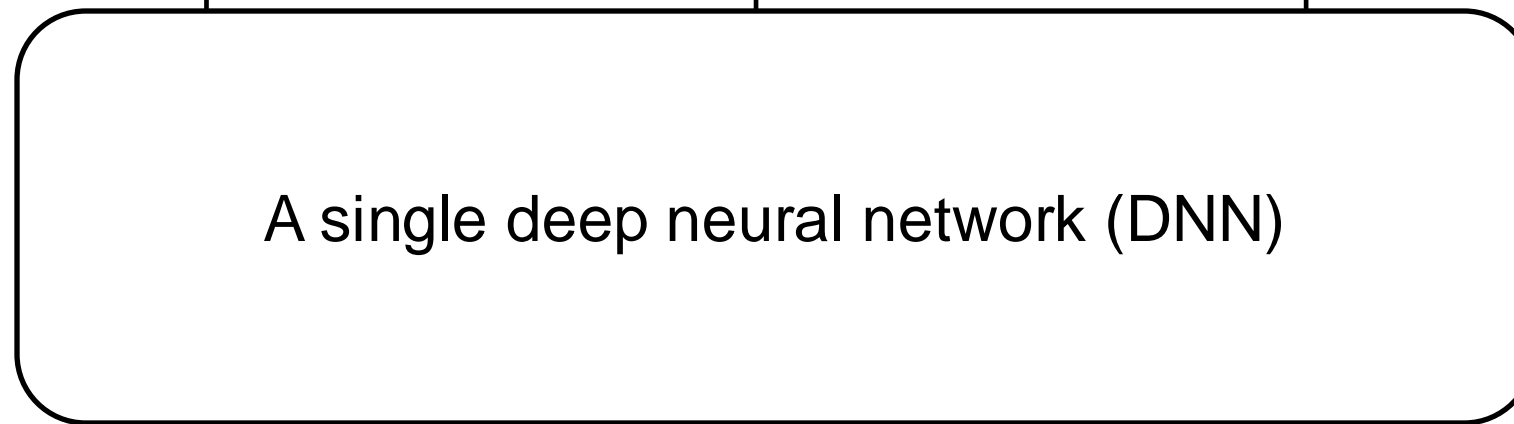


Background: spoofing-robust ASV (SASV)

□ Approach 1: end-to-end



✓ easy to get hands on
x no extra explanation



enroll

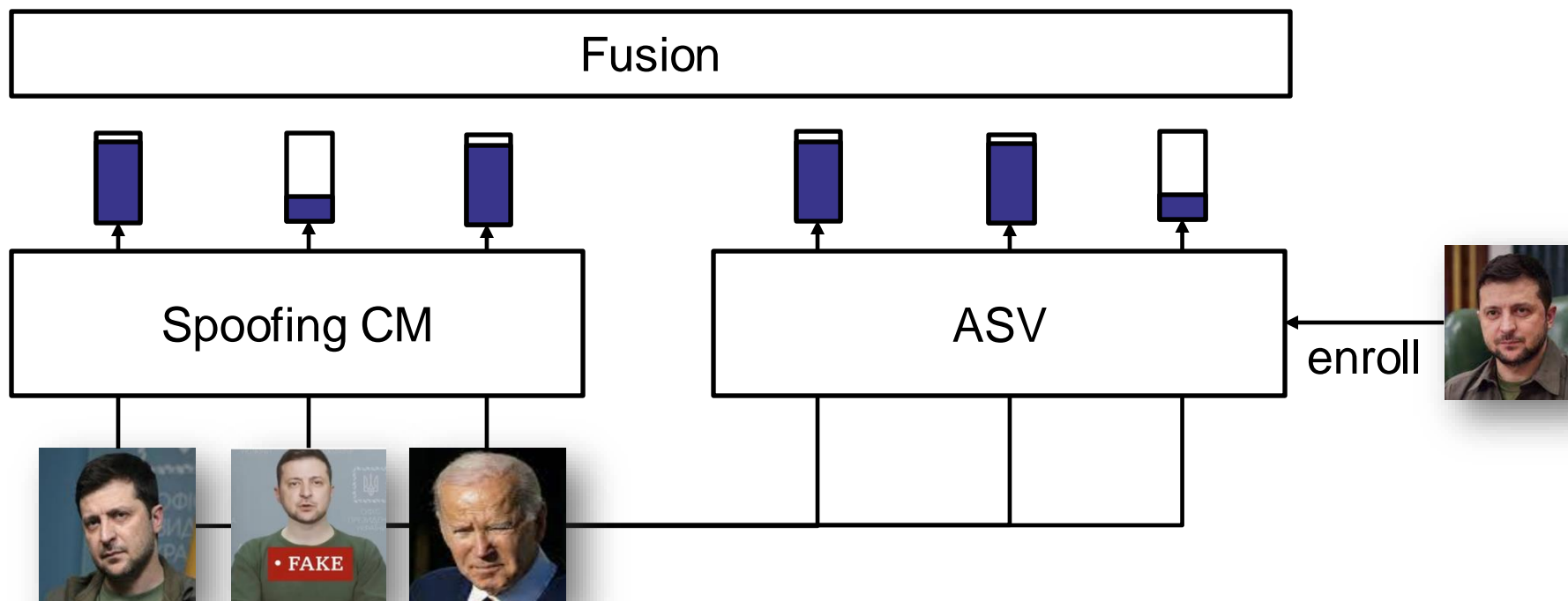


Background: spoofing-robust ASV (SASV)

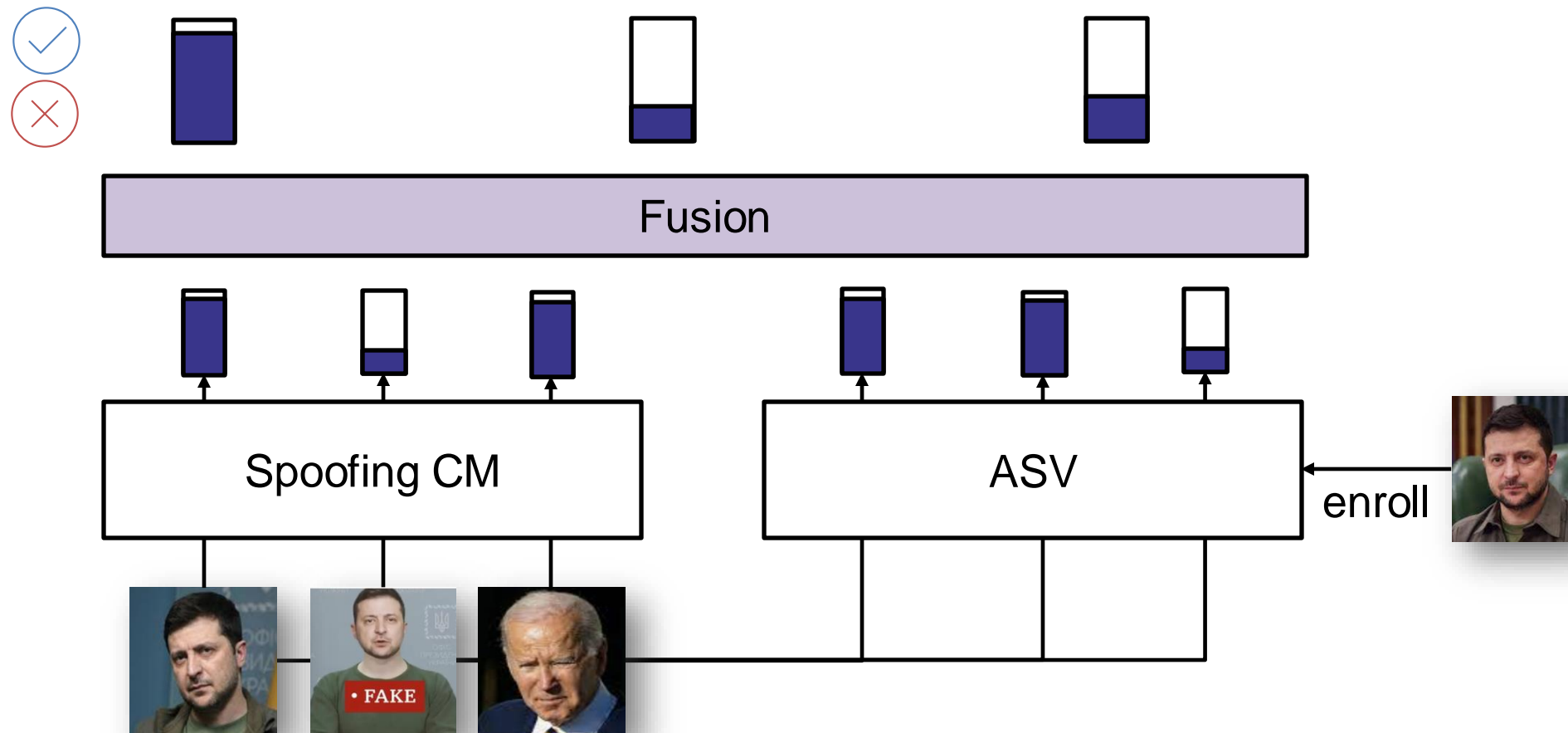
❑ Approach 2: fusion-based



- x technically demanding
- ✓ re-use CM & ASV
- ✓ extra explanations

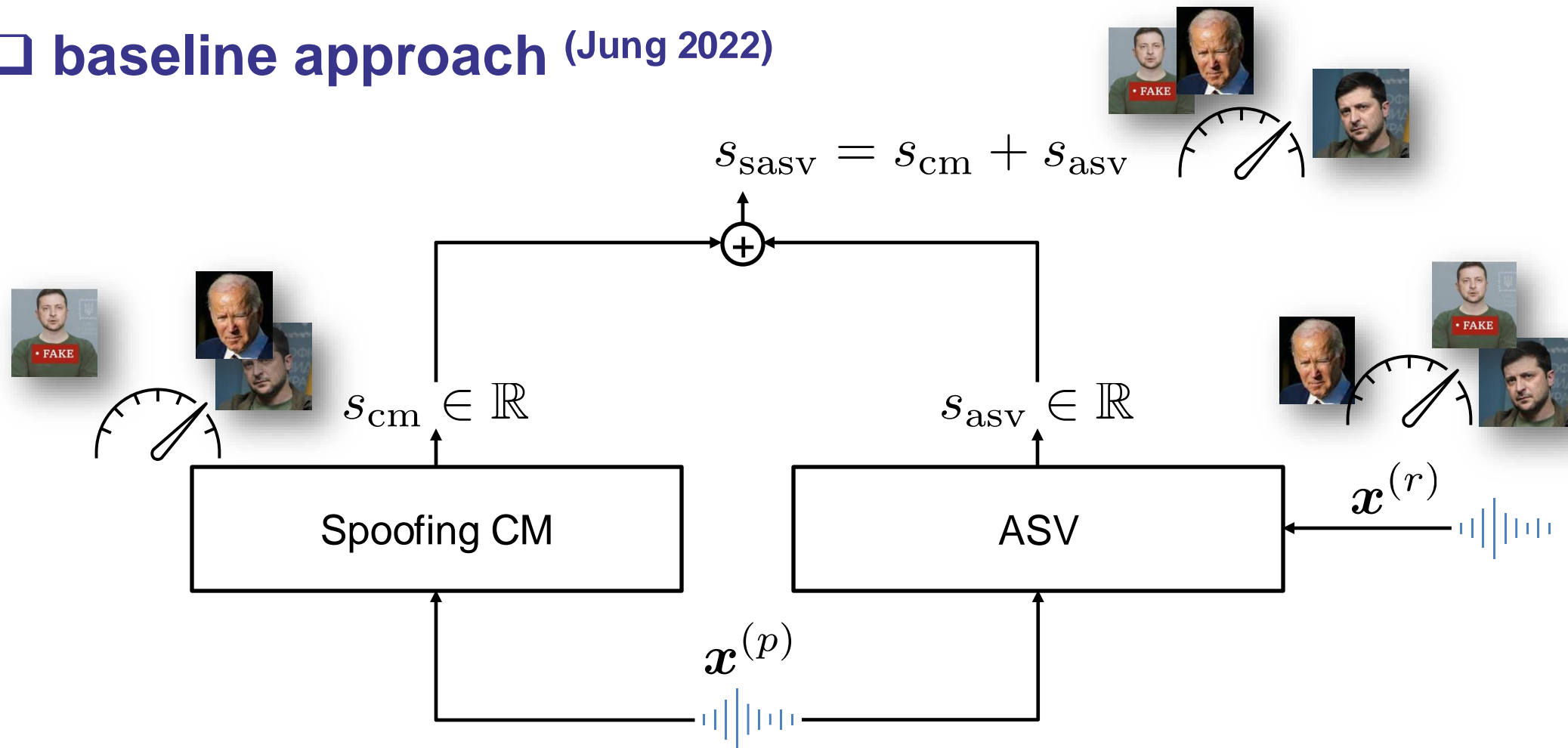


Question: how to *properly* fuse ASV and CM



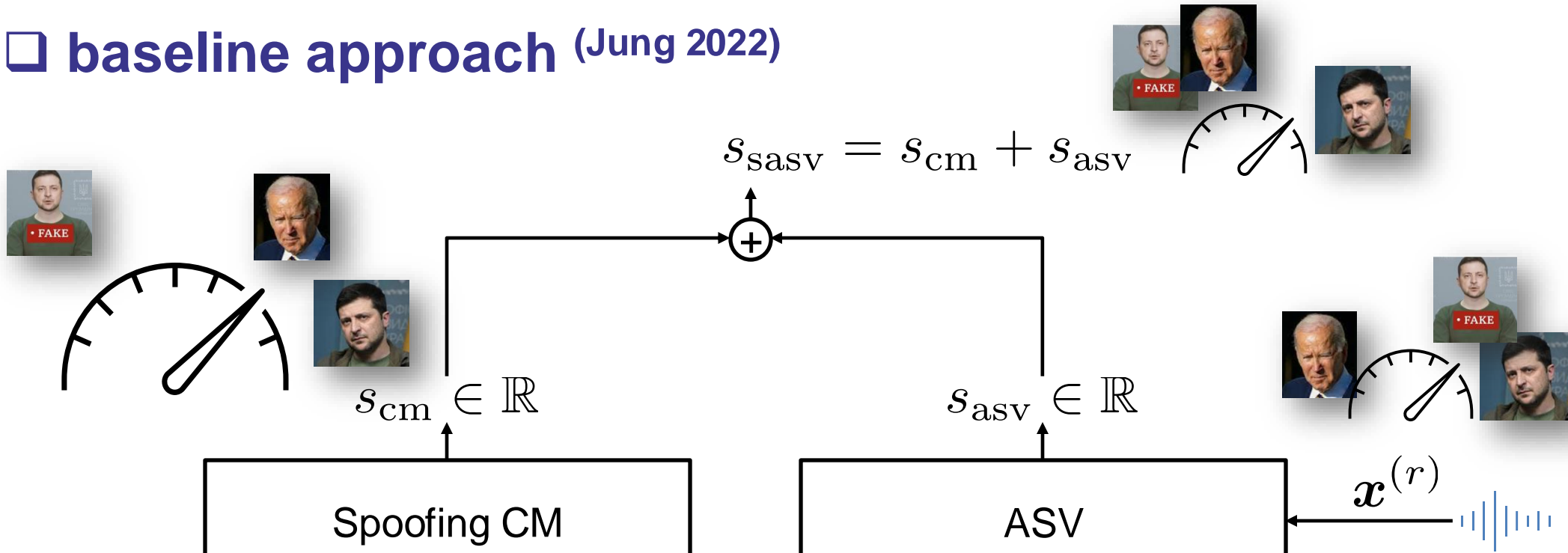
Question: how to *properly* fuse ASV and CM

□ baseline approach (Jung 2022)



Question: how to *properly* fuse ASV and CM

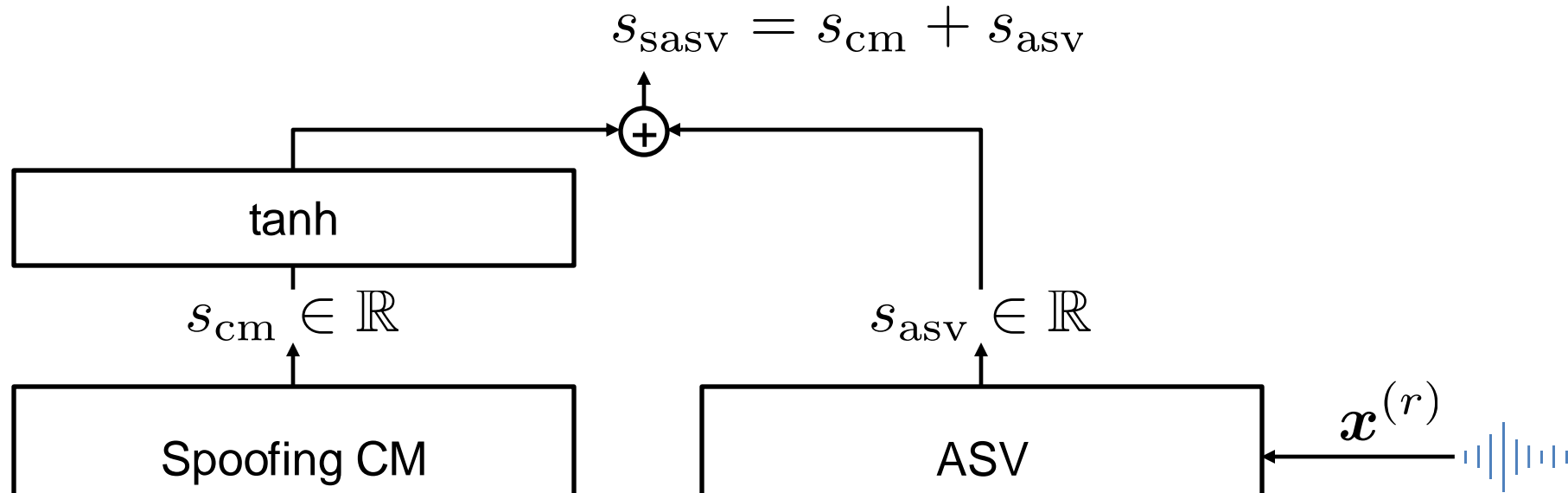
❑ baseline approach (Jung 2022)



? What to do if, say, $s_{cm} \in [-100, 100]$ $s_{asv} \in [-1, 1]$

Question: how to *properly* fuse ASV and CM

□ baseline approach (Jung 2022)



- ? What to do if, say, $s_{cm} \in [-100, 100]$ $s_{asv} \in [-1, 1]$
- ? Why not normalize both, why summation ...

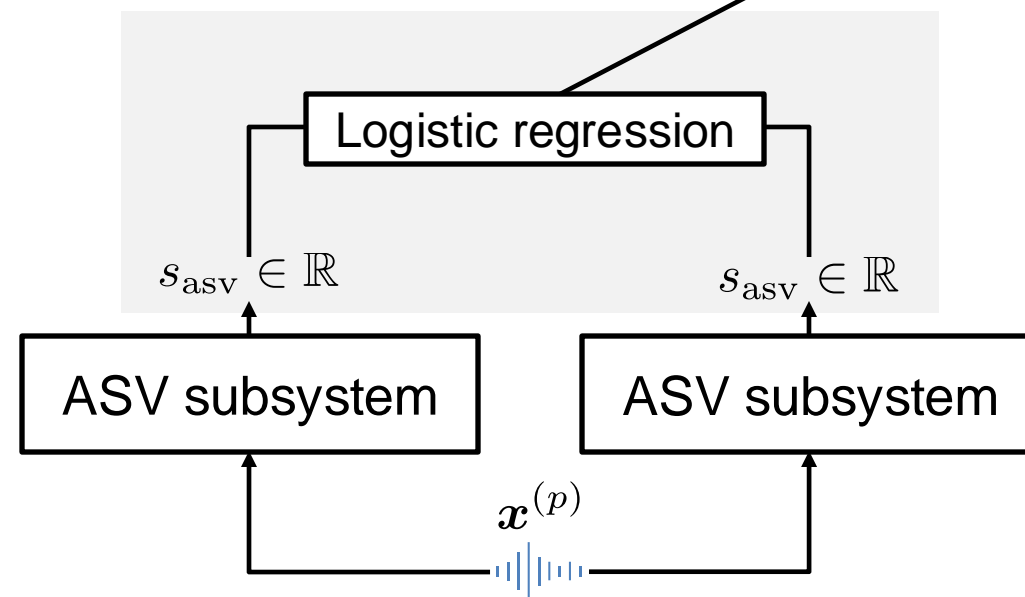
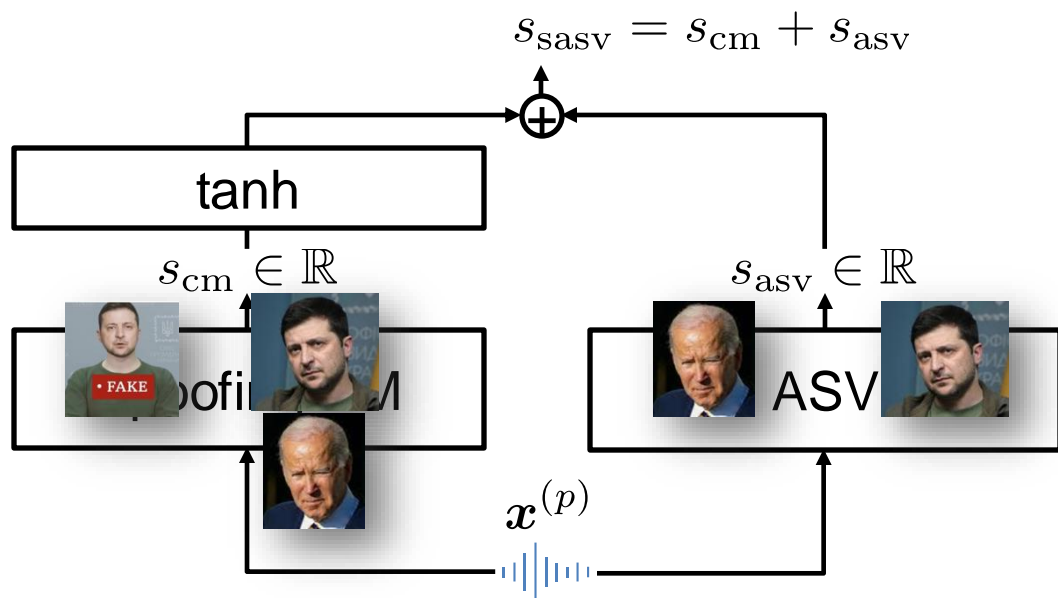
Any theory to support the good practice?

Answers by this work

❑ Fusion in SASV != fusion in ASV (or CM) ensemble (sec.2.1)

- Spoofing CM and ASV are dealing with different pairs of hypotheses
- A different theory is needed

$$\log \frac{P(H_{\text{tar}}|\mathbf{X})}{1 - P(H_{\text{tar}}|\mathbf{X})} = \log \frac{\pi_{\text{tar}}}{1 - \pi_{\text{tar}}} + \sum_{k=1}^K \text{llr}_{\text{non}}^{\text{tar}}(\mathbf{x}_k),$$



Answers by this work

❑ Fusion in SASV != fusion in ASV (or CM) ensemble (sec.2.1)

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We explain the practice in this talk

❑ Linear summation (Sec.2.2 – 2.4)

- Bayesian decision theory + compositional data analysis
- In practice: calibration + sum of CM and ASV LLRs

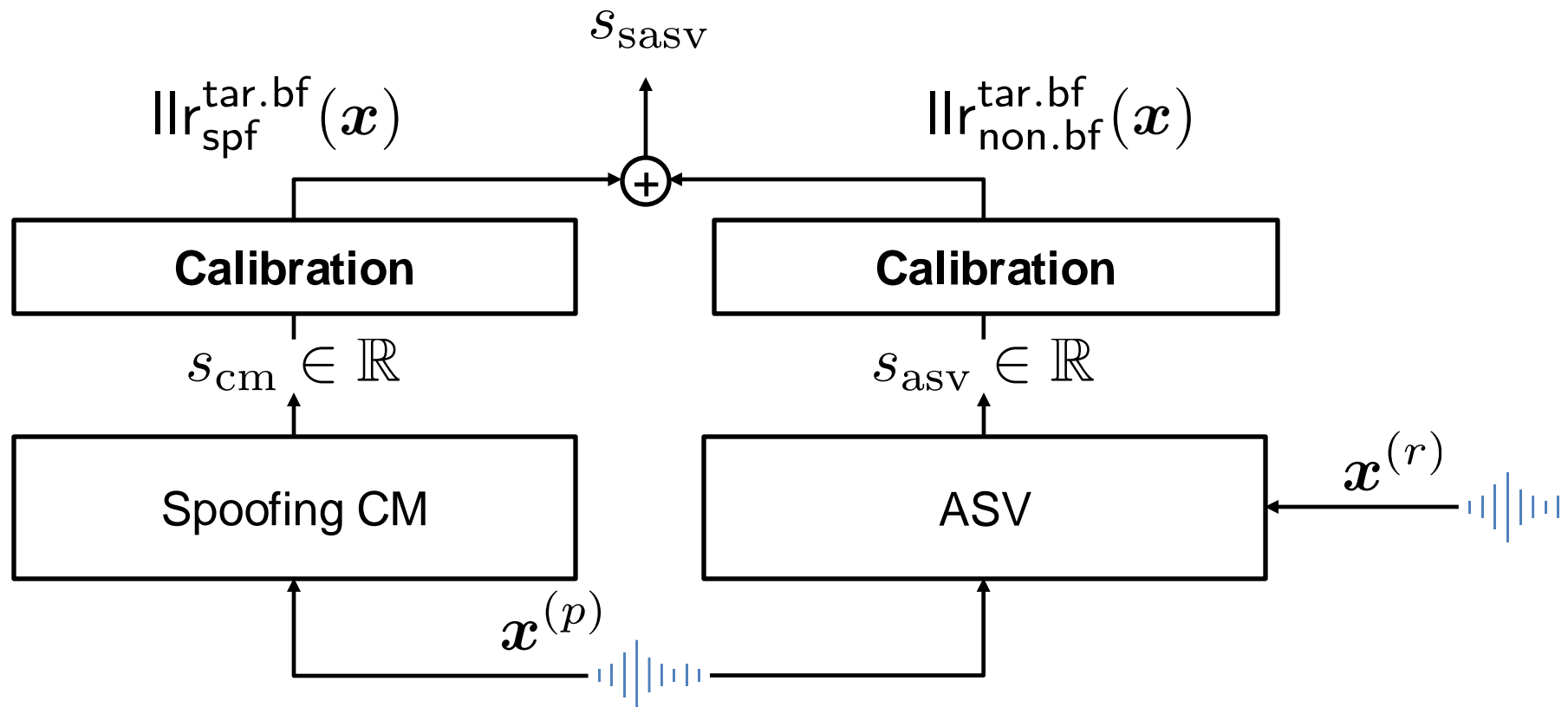
❑ Non-linear fusion (Sec.2.5)

- Bayesian decision theory (arxiv appendix)
 - the “optimal” solution to minimize a decision cost
- In practice: calibration & non-linear fusion

Method 1: linear fusion in good practice

❑ Score calibrations are needed

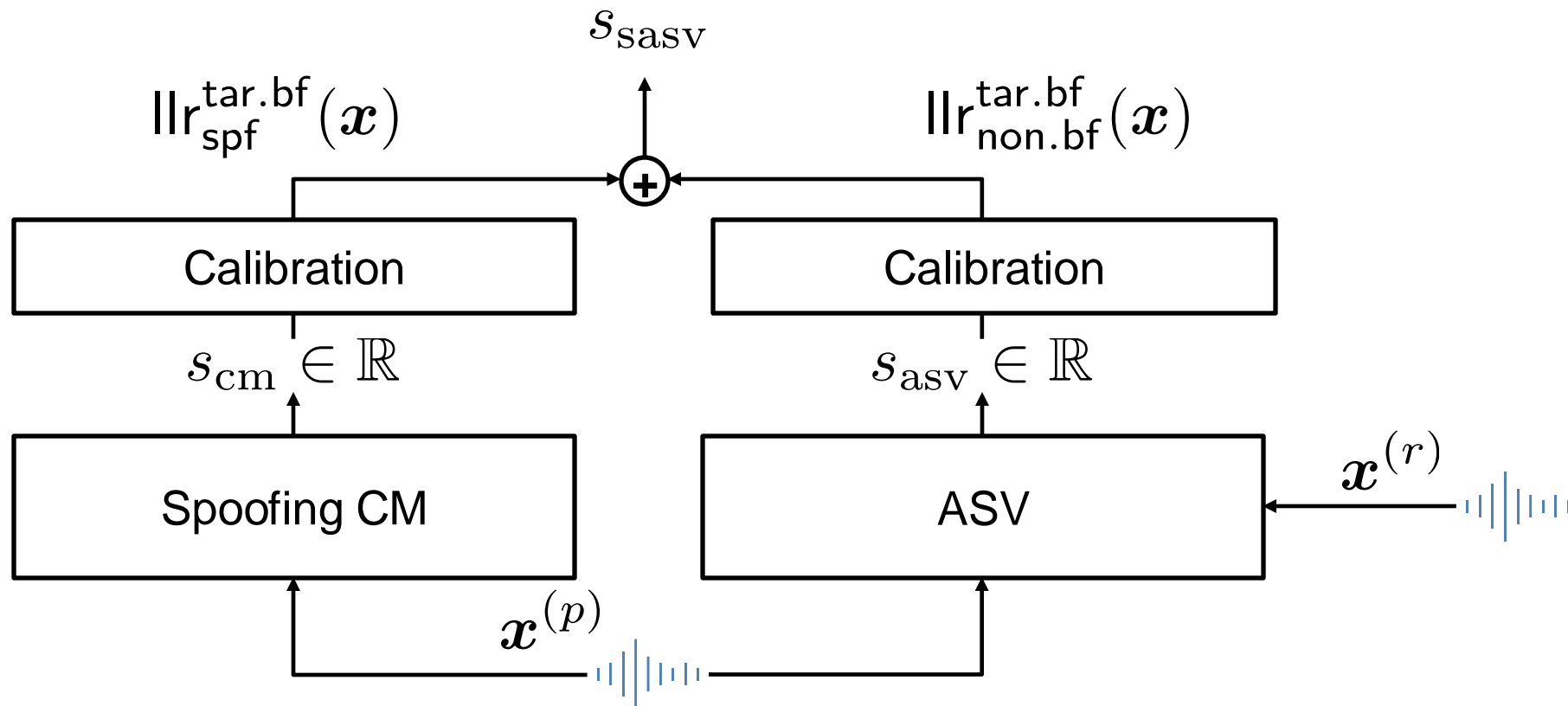
~~? Why normalize s_{cm} , not s_{asv}~~



Method 1: linear fusion in good practice

- ❑ Score calibrations are needed
- ❑ LLRs should be summed

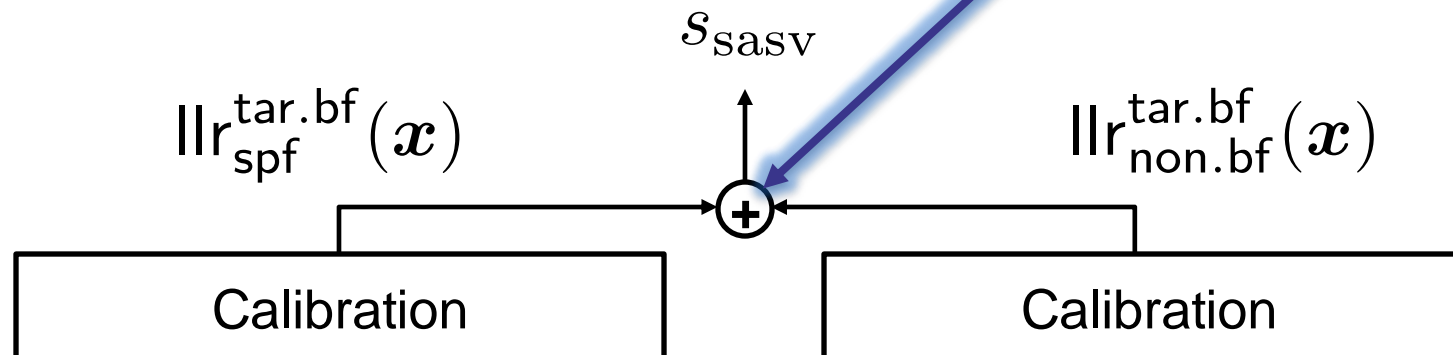
~~? Why normalize s_{cm} , not s_{asv}~~
? summation, product



Method 1: linear fusion in good practice

- ❑ Score calibrations are needed
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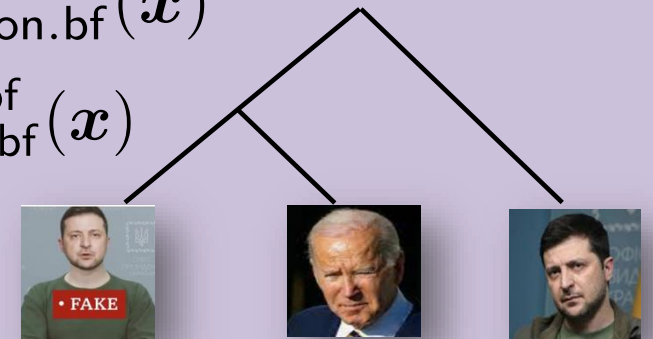
~~? Why normalize s_{cm} , not s_{asv}~~
? summation, product



*Three data classes but
binary decisions!
(sec 2.2 and appendix)*

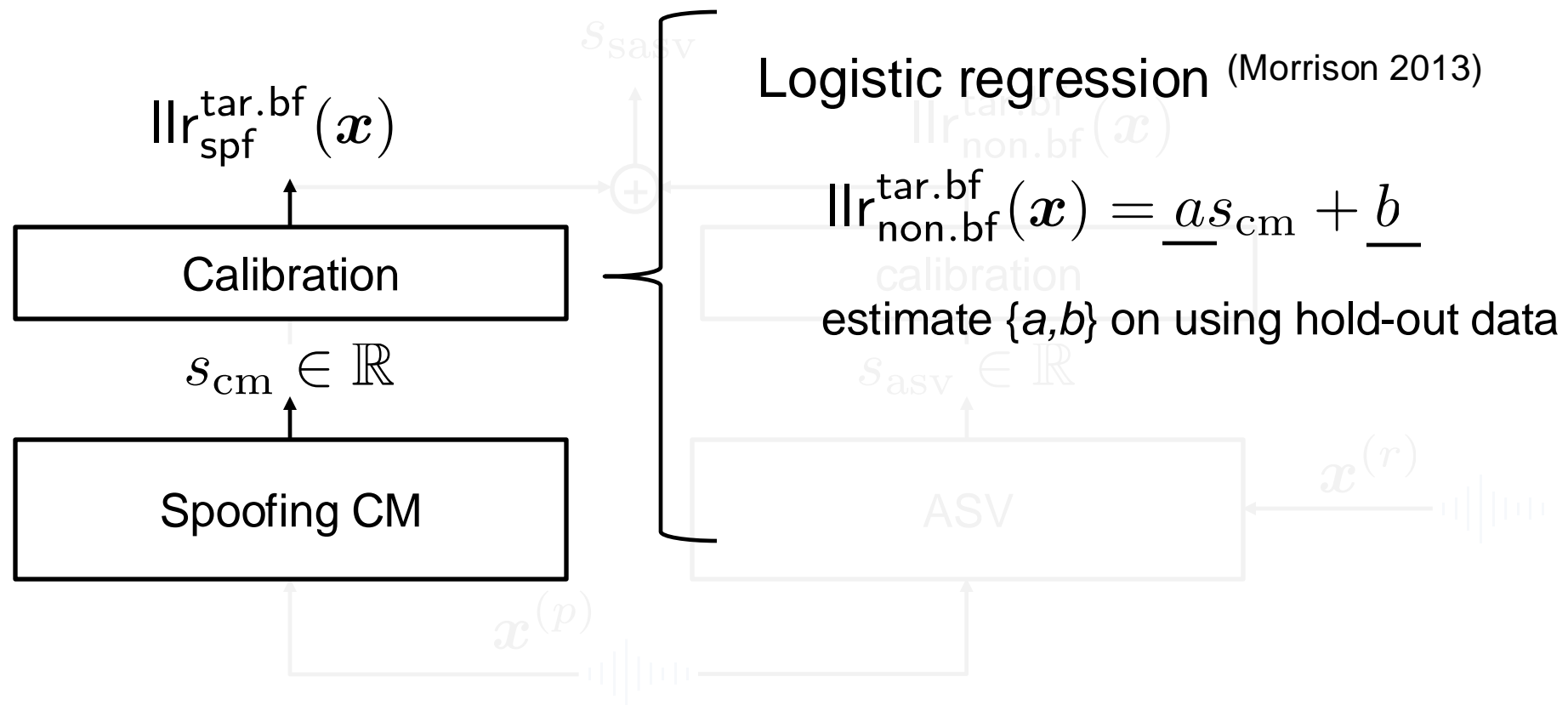
$$s_{\text{asv}} = \text{llr}_{\text{spf}}^{\text{tar.bf}}(x) + \text{llr}_{\text{non.bf}}^{\text{tar.bf}}(x)$$

$$s_{\text{cm}} = \text{llr}_{\text{spf}}^{\text{tar.bf}}(x) - \text{llr}_{\text{non.bf}}^{\text{tar.bf}}(x)$$



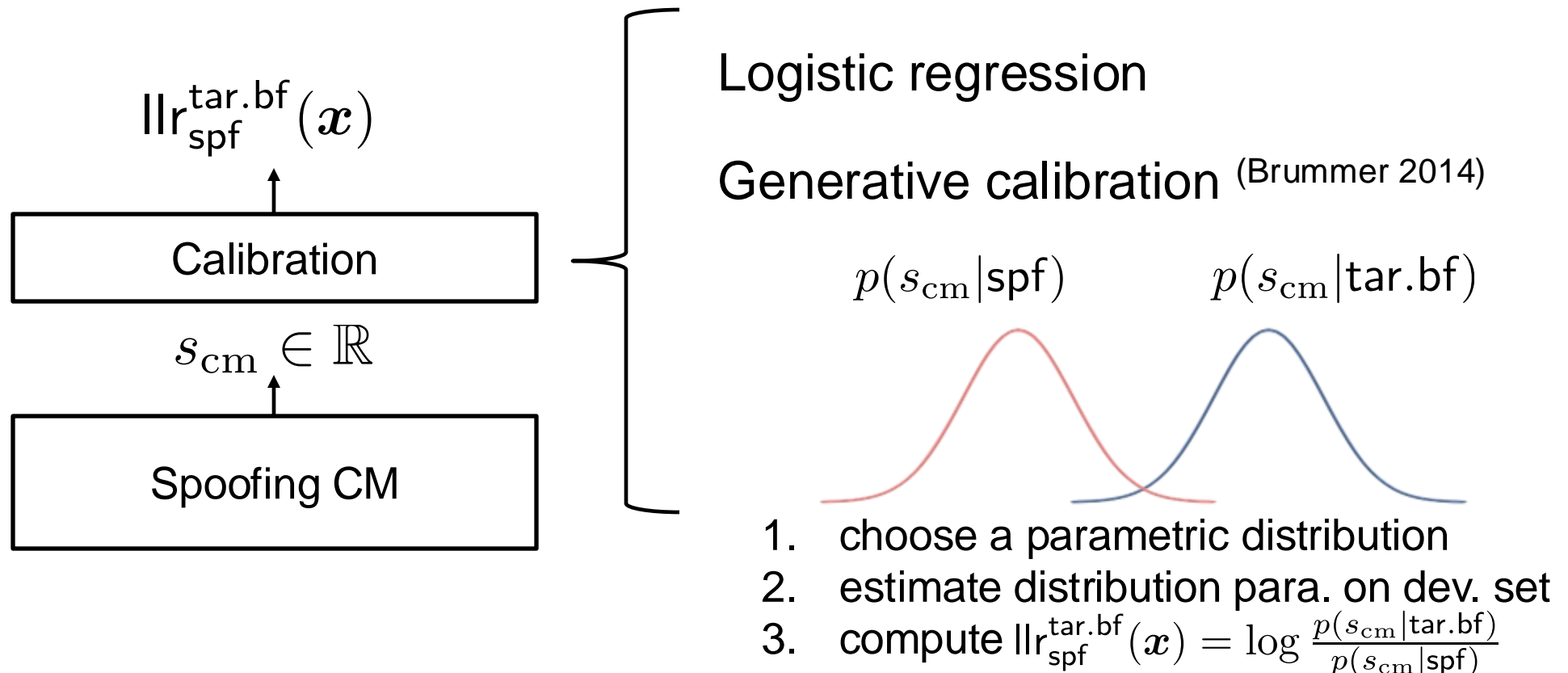
Method 1: linear fusion in good practice

□ Score calibration – nothing new



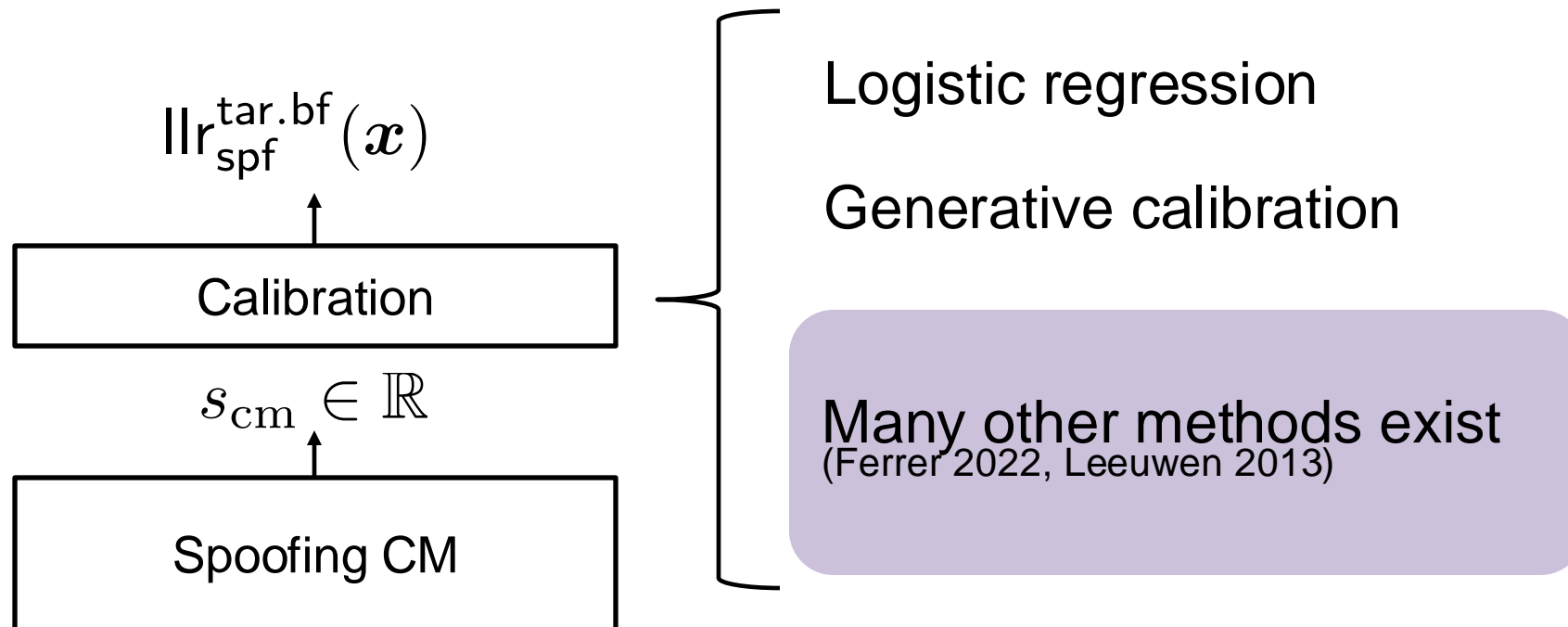
Method 1: linear fusion in good practice

□ Score calibration – nothing new



Method 1: linear fusion in good practice

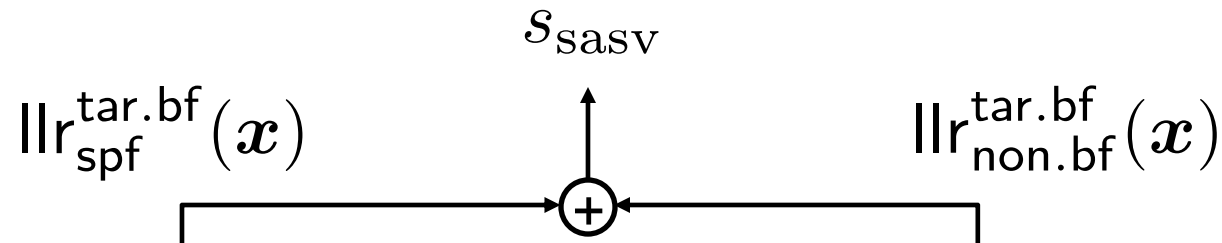
□ Score calibration – nothing new








Method 1: linear fusion in good practice

❑ Is linear fusion optimal for decision making?

- No



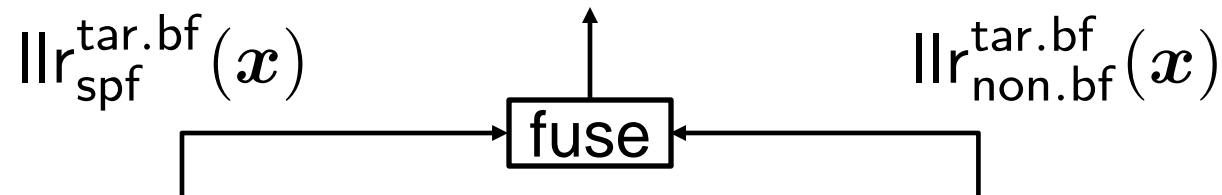
*See more in Sec2.5
& Appendix*

Cost		
Bona fide matched 	0	Cmiss
Bona fide unmatched 	Cfa	0
Spoofed 	Cfa	0






Method 2: non-linear fusion is better

□ Non-linear fusion minimizes the cost

$$s_{\text{sasv}} = -\log \left[(1 - \rho) e^{-\text{llr}_{\text{non.bf}}^{\text{tar.bf}}} + \rho e^{-\text{llr}_{\text{spf}}^{\text{tar.bf}}} \right] \quad \text{for } C_{\text{fa}} = C_{\text{miss}}$$



See more in Sec2.5
& Appendix

Cost		
Bona fide matched 	0	Cmiss
Bona fide unmatched 	Cfa	0
Spoofed 	Cfa	0

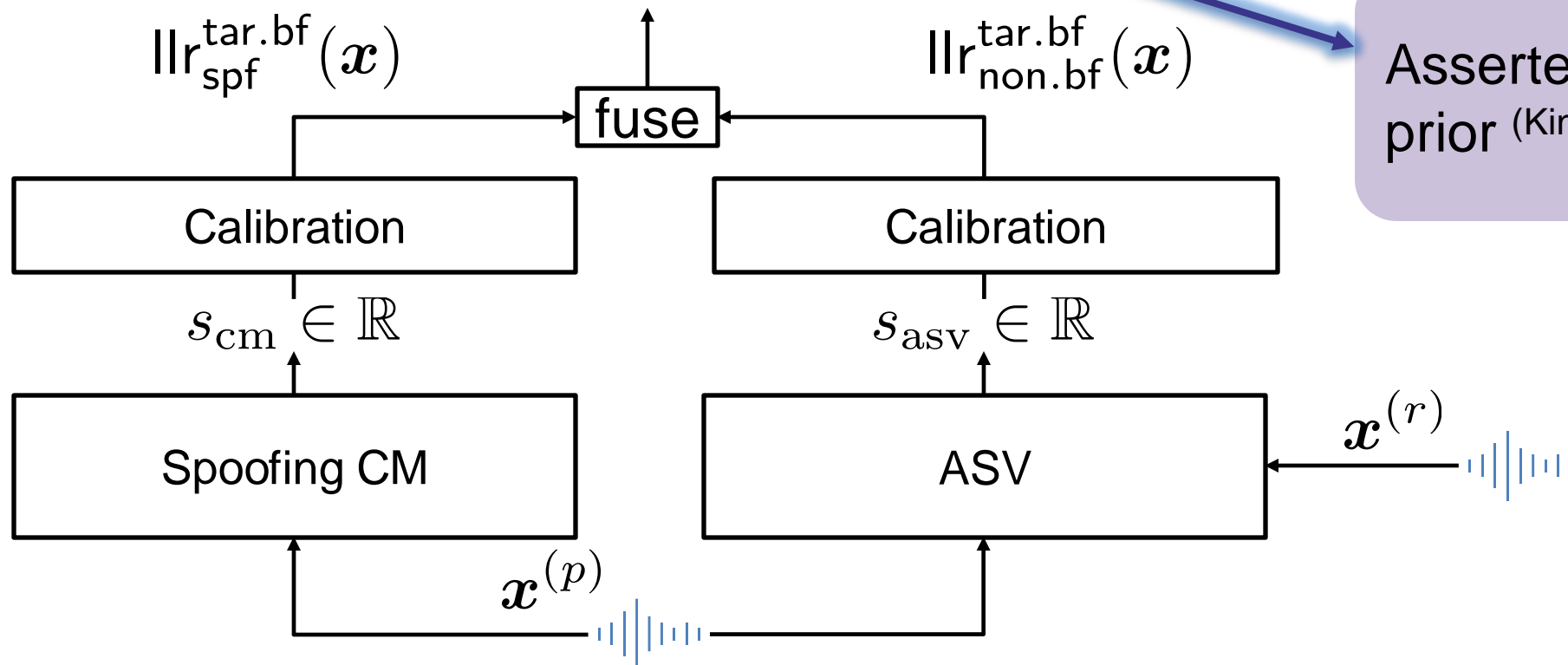
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$$s_{\text{sasv}} = -\log \left[(1 - \rho) e^{-\text{llr}_{\text{non.bf}}^{\text{tar.bf}}} + \rho e^{-\text{llr}_{\text{spf}}^{\text{tar.bf}}} \right]$$

for Cfa=Cmiss

Asserted spoofing prior (Kinnunen 2023)

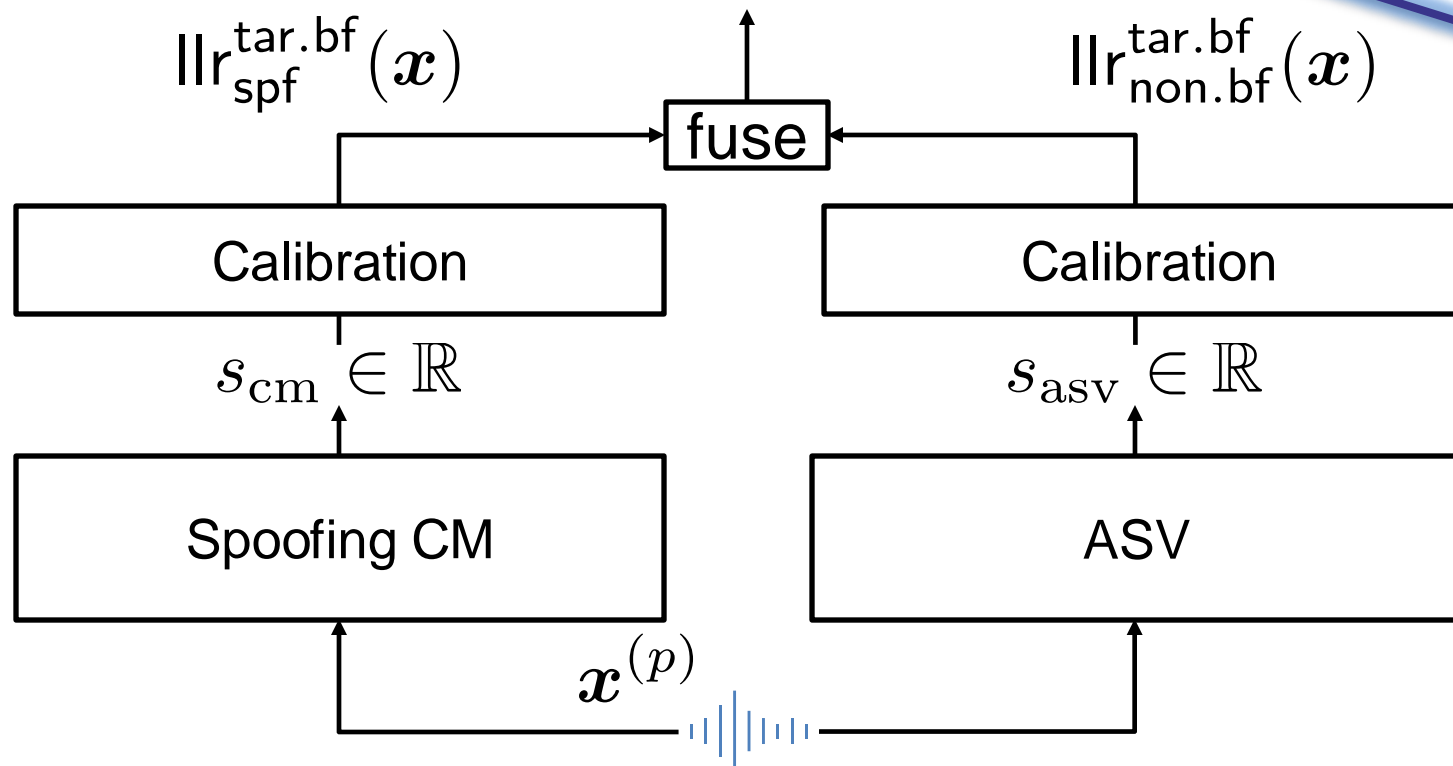


Method 2: non-linear fusion is better

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for Cfa=Cmiss

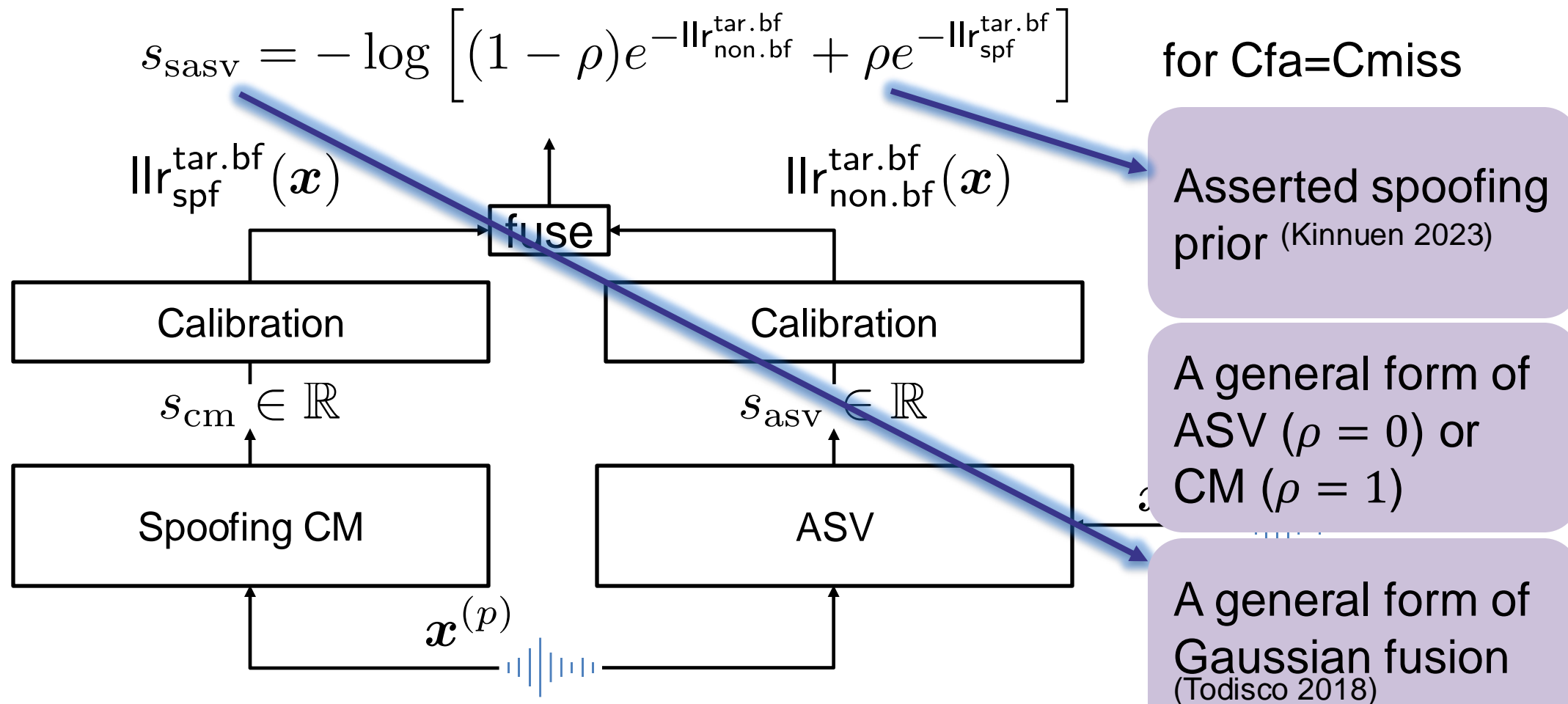


Asserted spoofing prior (Kinnunen 2023)

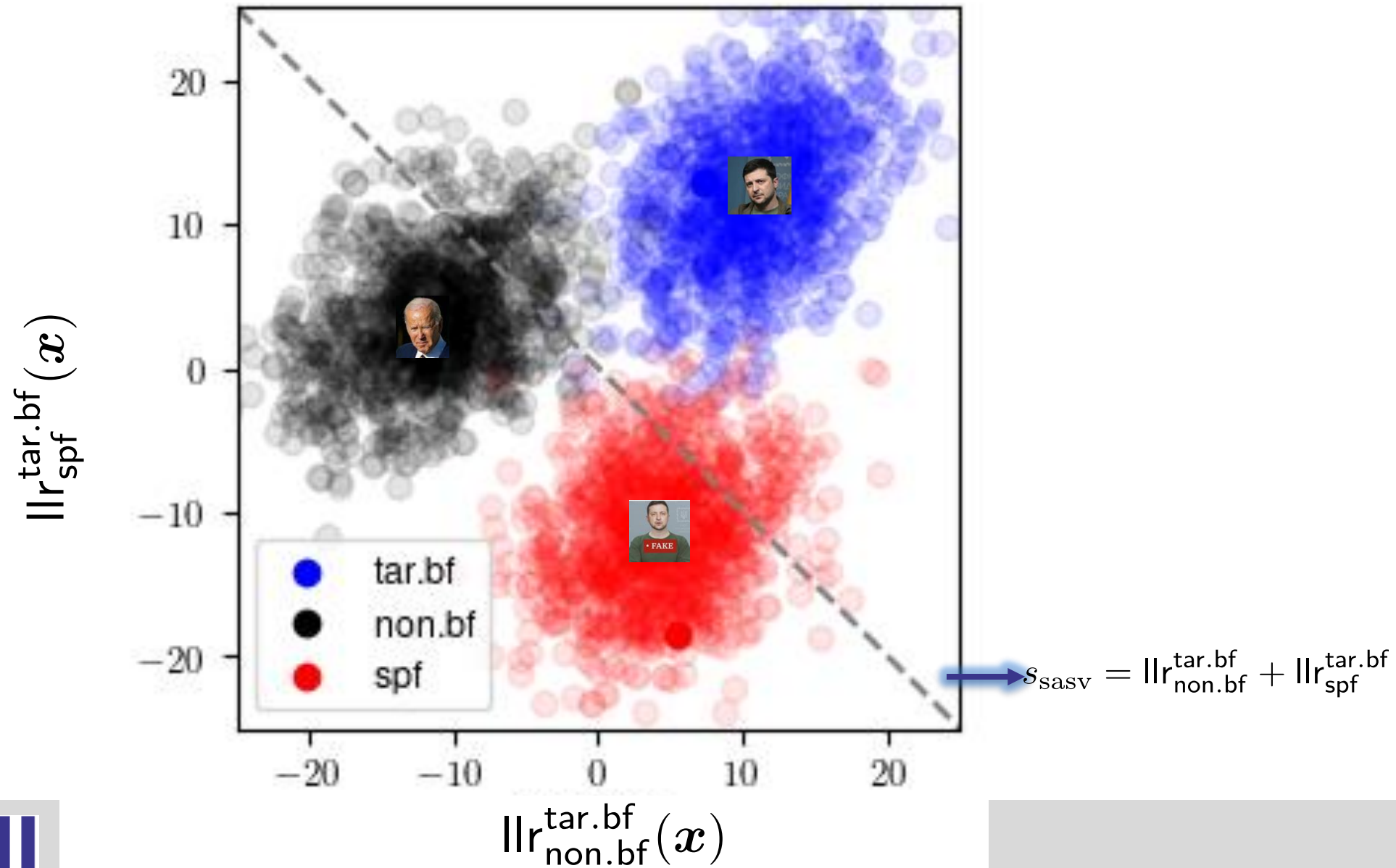
A general form of ASV ($\rho = 0$) or CM ($\rho = 1$)

Method 2: non-linear fusion is better

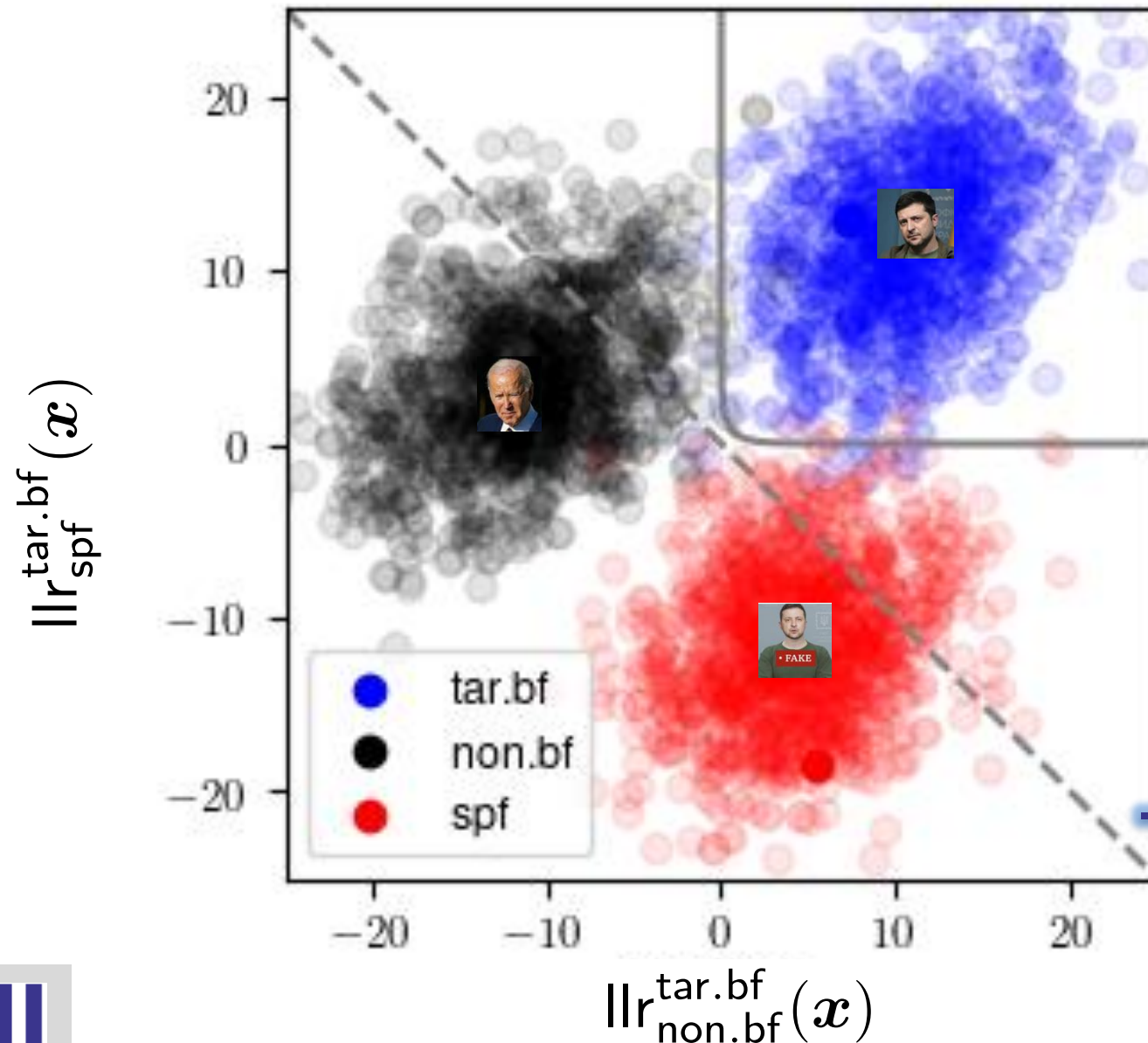
□ Non-linear fusion minimizes the cost



Demo on toy data set



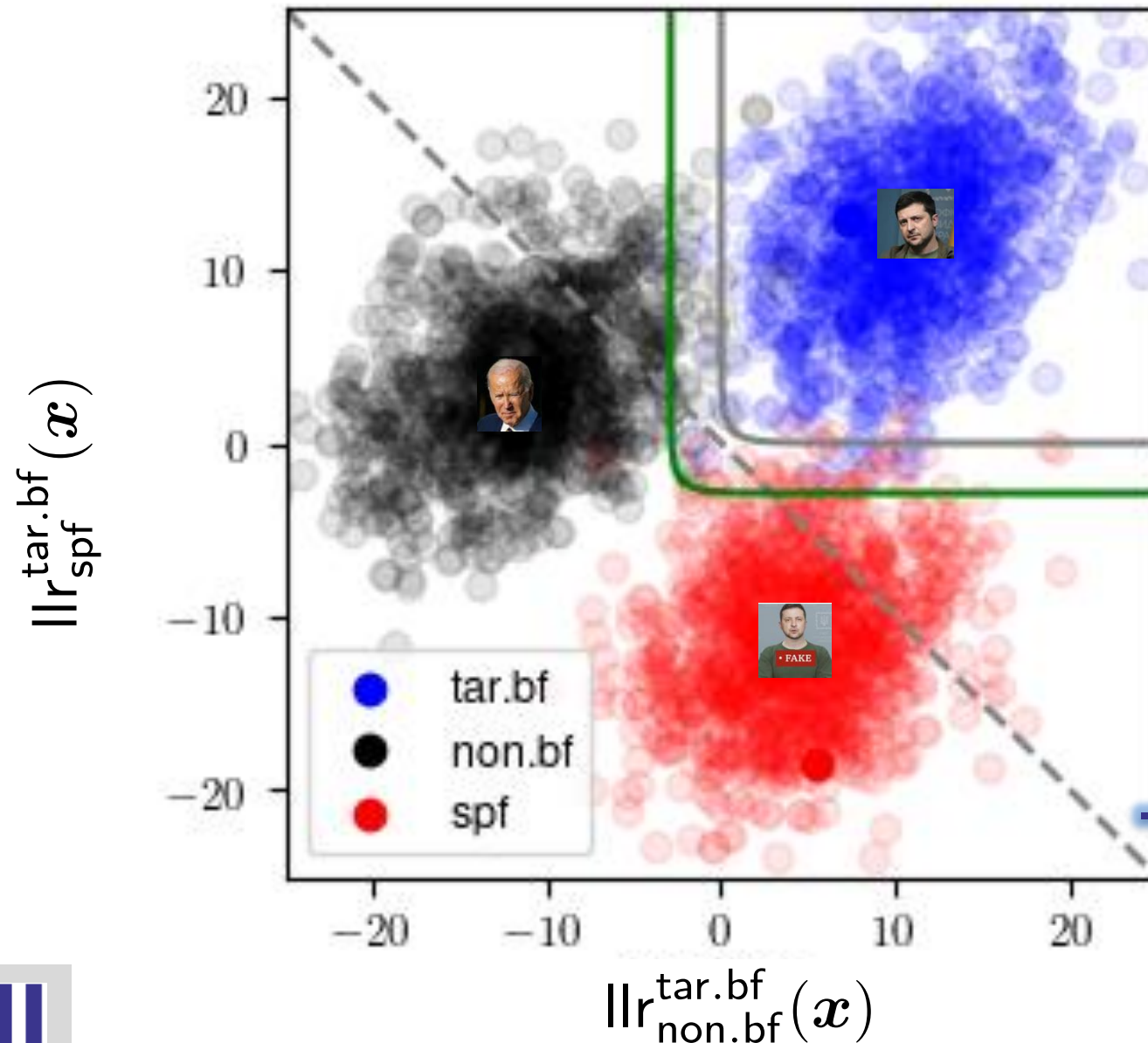
Demo on toy data set



$$s_{\text{sasv}} = -\log \left[(1 - \rho) e^{-\text{llr}_{\text{non.bf}}^{\text{tar.bf}}} + \rho e^{-\text{llr}_{\text{spf}}^{\text{tar.bf}}} \right]$$

$$s_{\text{sasv}} = \text{llr}_{\text{non.bf}}^{\text{tar.bf}} + \text{llr}_{\text{spf}}^{\text{tar.bf}}$$

Demo on toy data set



$$s_{\text{sasv}} = -\log \left[(1 - \rho) e^{-\|r_{\text{non.bf}}^{\text{tar.bf}}(x)} + \rho e^{-\|r_{\text{spf}}^{\text{tar.bf}}(x)} \right]$$

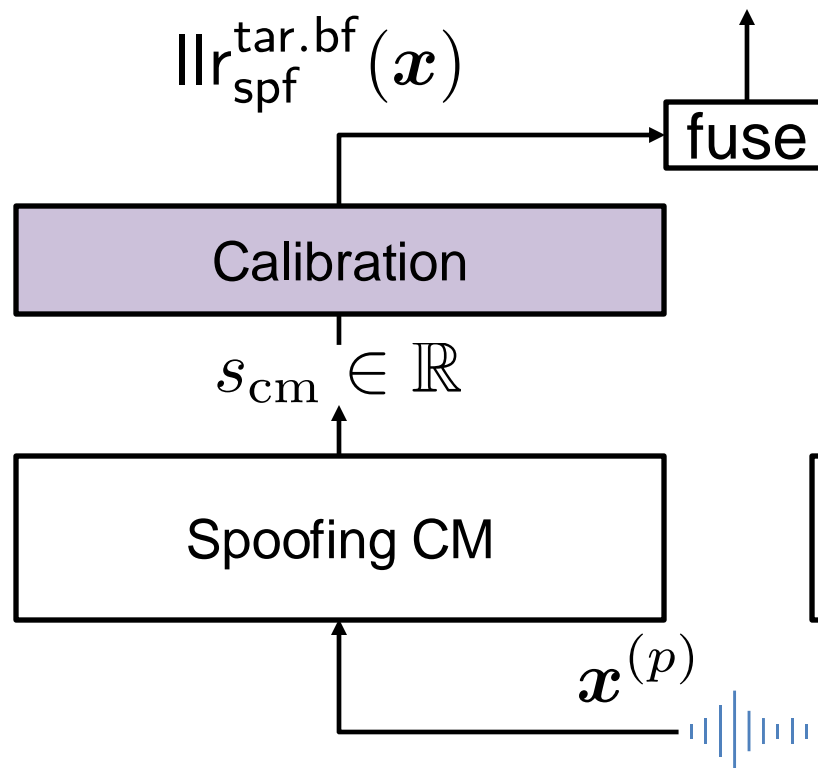
different ρ

$$s_{\text{sasv}} = \|r_{\text{non.bf}}^{\text{tar.bf}}(x) + \|r_{\text{spf}}^{\text{tar.bf}}(x)$$

Recap the practices

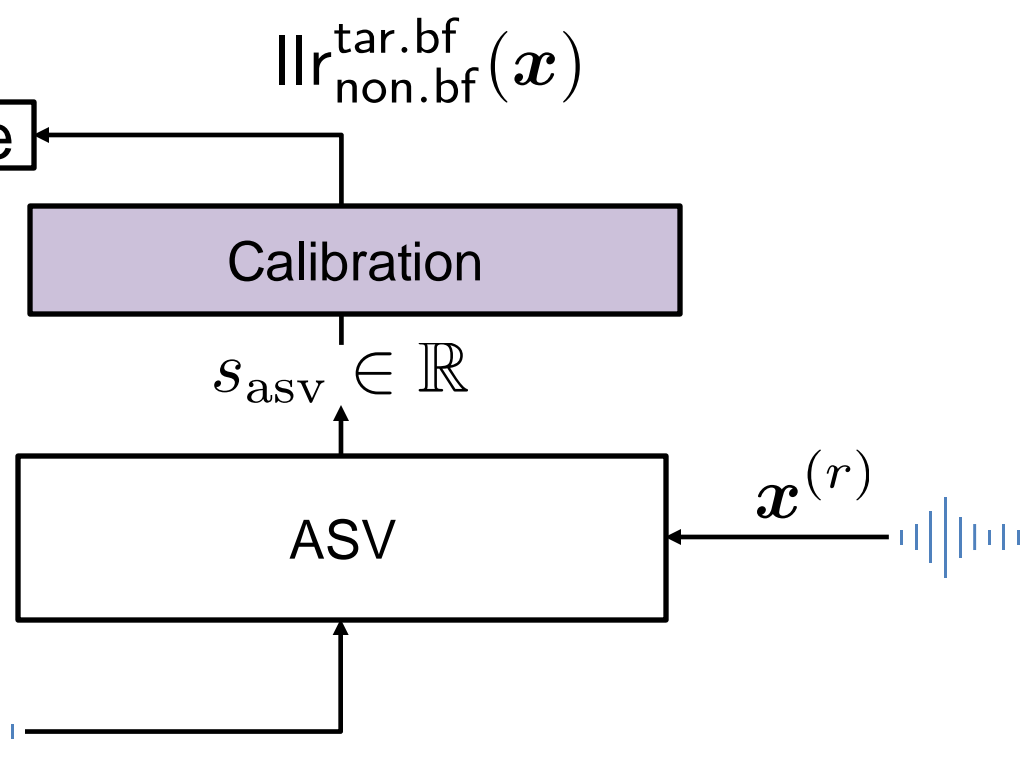
Linear fusion

$$s_{\text{sasv}} = \text{llr}_{\text{non.bf}}^{\text{tar.bf}} + \text{llr}_{\text{spf}}^{\text{tar.bf}}$$



Non-linear fusion

$$s_{\text{sasv}} = -\log \left[(1 - \rho) e^{-\text{llr}_{\text{non.bf}}^{\text{tar.bf}}} + \rho e^{-\text{llr}_{\text{spf}}^{\text{tar.bf}}} \right]$$



Experiments

□ Data

- SASV 2022 challenge database, official protocols (Jung 2022)

□ Systems

- All use *pre-trained* ASV and CM from SASV 2022 B1 (Jung 2022)
- Systems differ in score calibration & fusion

□ Misc

- Training & evaluation in six rounds
- Averaged results are reported

Experiments



worse



better

ID	B1	B1c	L2	L2c	L3	L3c	B1v2	Post
Fusion	linear		linear		non-linear			
Calibration	×	✓	×	✓	×	✓	×	×
SASV-EER (%)	20.46	2.73	3.31	1.56	1.44	1.43	1.60	1.55
conf. ($\alpha = 5\%$)	± 0.40	± 0.27	± 0.31	± 0.23	± 0.23	± 0.23	± 0.22	± 0.24
Cllr	2.17	1.09	1.04	0.14	0.18	0.16	0.96	0.84
Cllr _{min}	0.52	0.11	0.13	0.07	0.06	0.07	0.08	0.07
Cllr _{calib}	1.64	0.98	0.91	0.07	0.11	0.10	0.88	0.78
t-EER (%)	2.10	2.10	1.68	1.68	1.68	1.68	2.19	2.21

SASV-
EER
(Jung2022)

other
metrics

Systems with different fusion &
calibration methods

From other
papers

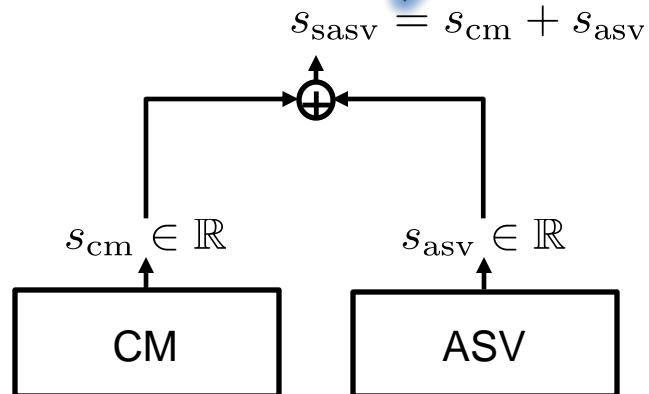
Experiments

ID	B1	B1c	L2	L2c	L3	L3c	B1v2	Post
Fusion	linear		linear					
Calibration	×	✓	×	✓	×	✓	×	×
SASV-EER (%)	20.46	2.73	3.31	1.56	1.44	1.43	1.60	1.55
conf. ($\alpha = 5\%$)	± 0.40	± 0.27	± 0.31	± 0.23	± 0.23	± 0.23	± 0.22	± 0.24

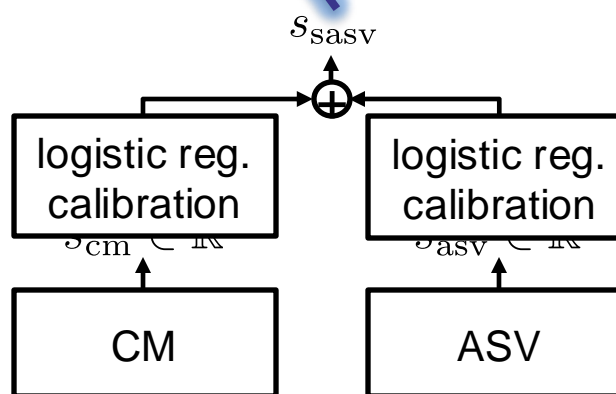
no
calibration

log.reg.
calibration

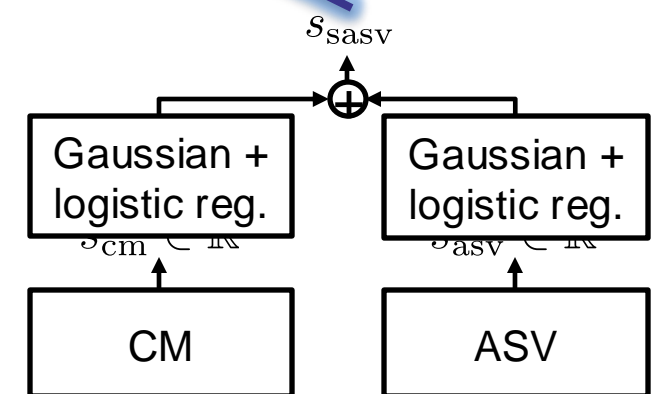
log.reg. + Gaussian
calibration



baseline



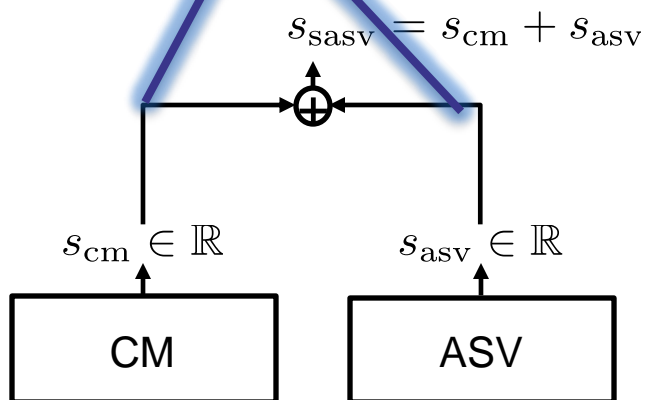
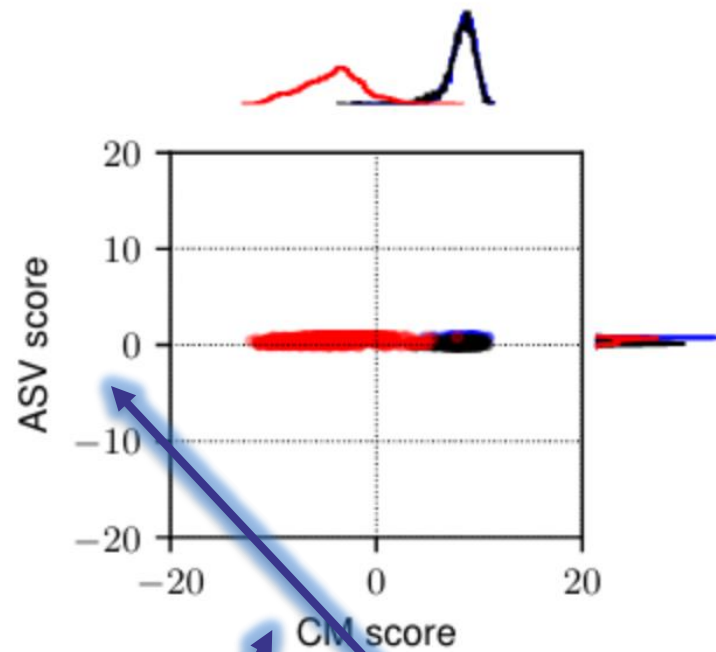
good linear fusion



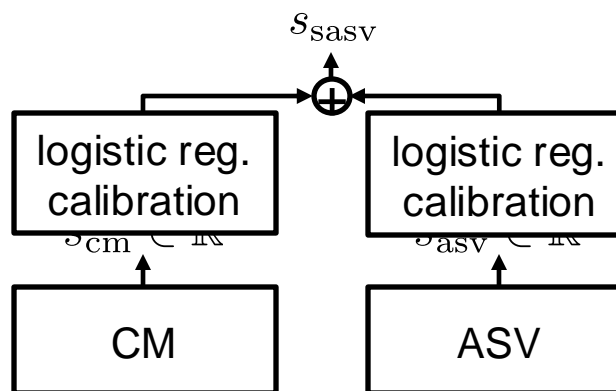
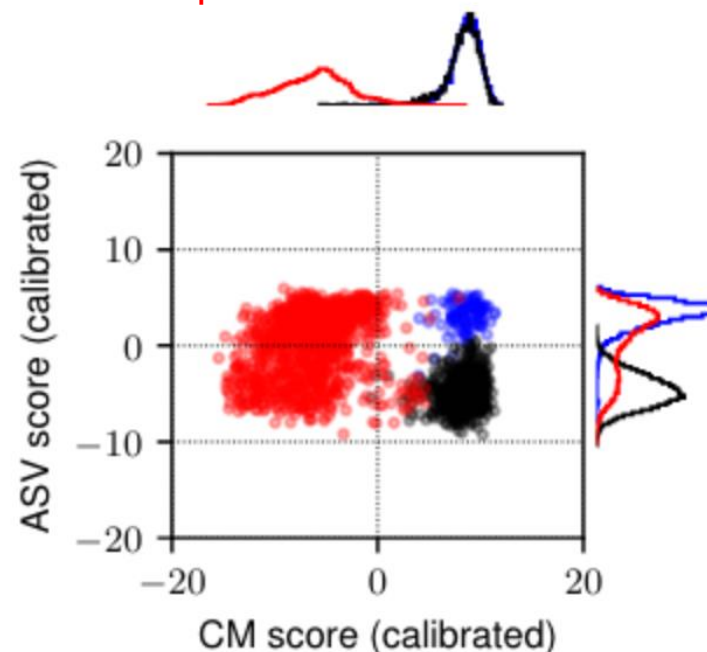
good linear fusion 31

Experiments

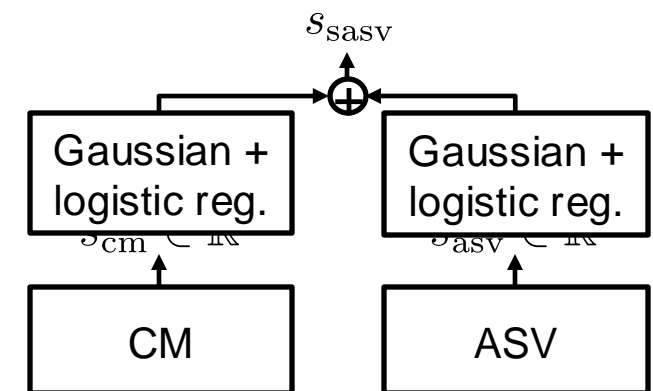
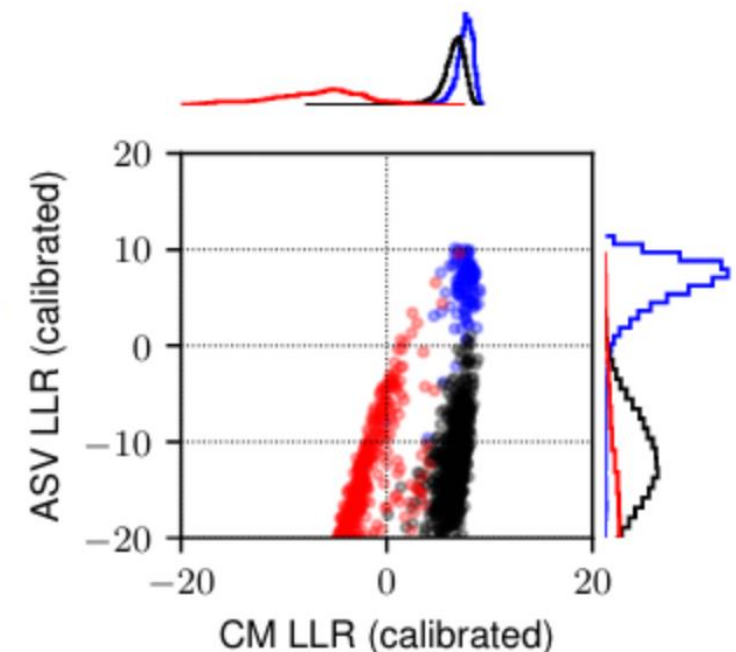
bona fide matched
bona fide unmatched
spoofed



baseline



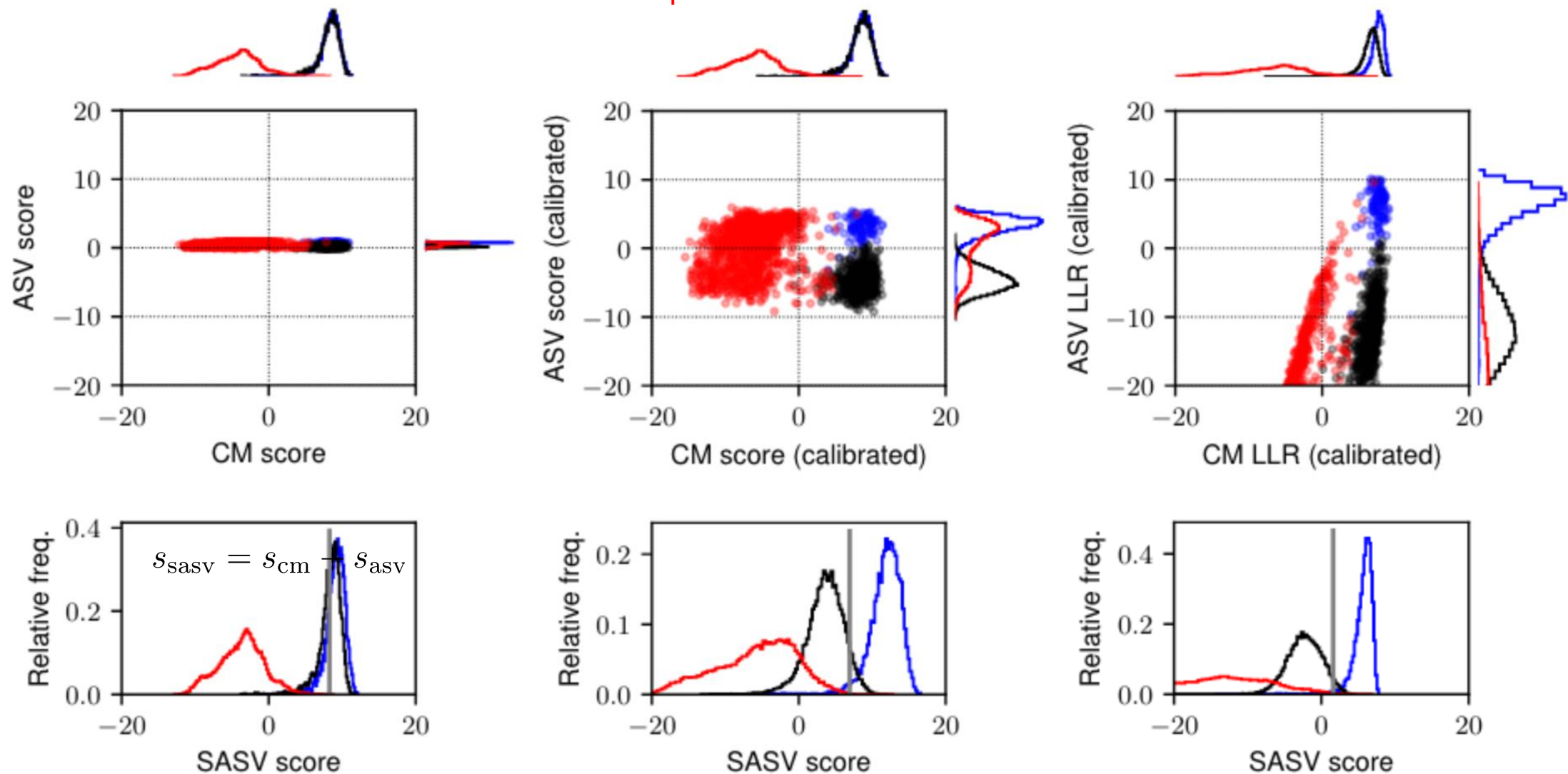
good linear fusion



good linear fusion 32

Experiments

bona fide matched
bona fide unmatched
spoofed

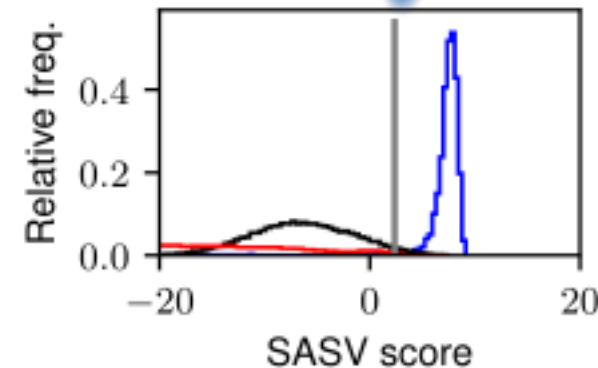
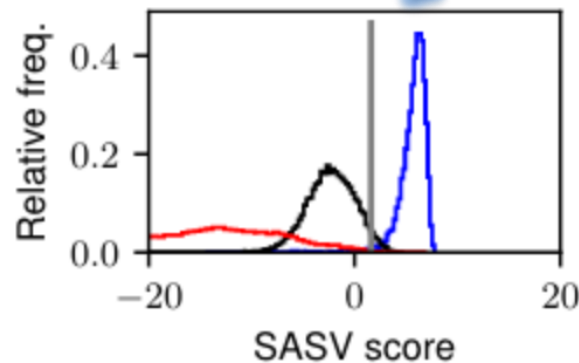


Experiments

ID	B1	B1c	L2	L2c	L3	L3c		B1v2	Post
Fusion				linear		non-linear		(Jung 2022)	(Zhang 2022)
Calibration	×	✓	×	✓	×	✓		×	×
SASV-EER (%)	20.46	2.73	3.31	1.56	1.44	1.43		1.60	1.55
conf. ($\alpha = 5\%$)	± 0.40	± 0.27	± 0.31	± 0.23	± 0.23	± 0.23		± 0.22	± 0.24

The difference is small on this database

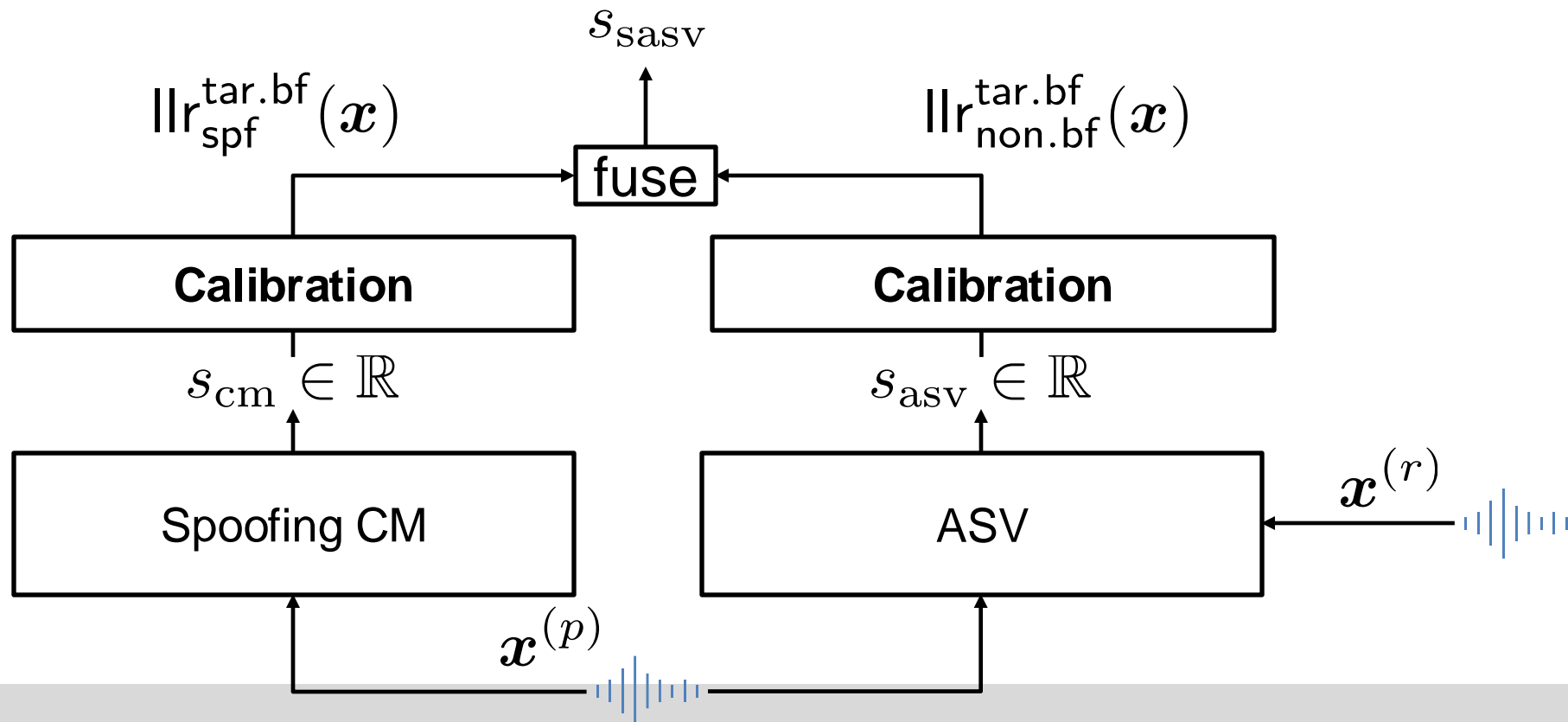
good linear fusion



good non-linear fusion

Main messages

- ❑ Fusion SASV != fusion of ASV or CM ensemble
- ❑ Linear and non-linear can be supported by theory
- ❑ Calibration affects discrimination



Pointers

❑ Evaluation using the same Bayes decision cost

Hye-jin Shim, Jee-weon Jung, Tomi Kinnunen, Nicholas Evans, Jean-Francois Bonastre, and Itshak Lapidot. 2024. **a-DCF: an architecture agnostic metric with application to spoofing-robust speaker verification**. In Proc. Odyssey, 2024. 158–164.
<https://doi.org/10.21437/odyssey.2024-23>

❑ SOTA ASV is not robust to spoofing attacks

Jee-weon Jung, Xin Wang, Nicholas Evans, Shinji Watanabe, Hye-jin Shim, Hemlata Tak, Sidhhant Arora, Junichi Yamagishi, and Joon Son Chung. 2024. **To what extent can ASV systems naturally defend against spoofing attacks?** In Proc. Interspeech, 2024. .

A4-05.5

❑ The non-linear fusion has been used by many teams in ASVspoof 5 challenge

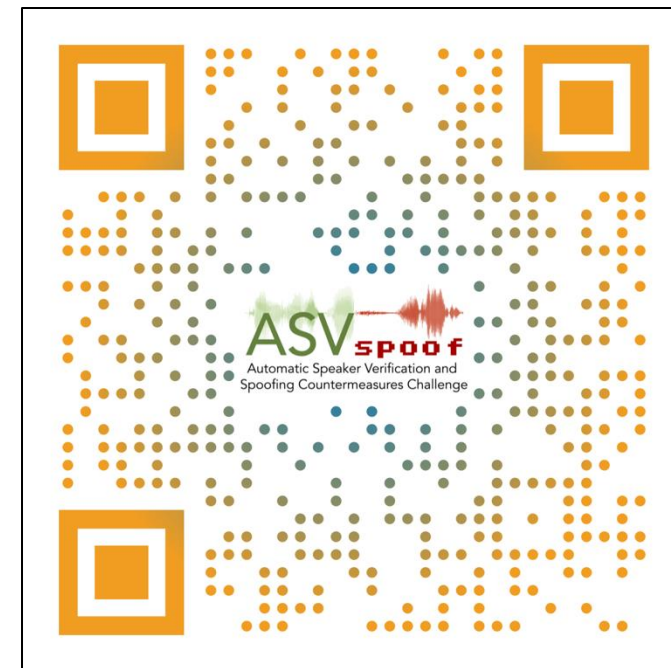
Thank you



Code & Jupyter notebook
step-by-step explanation



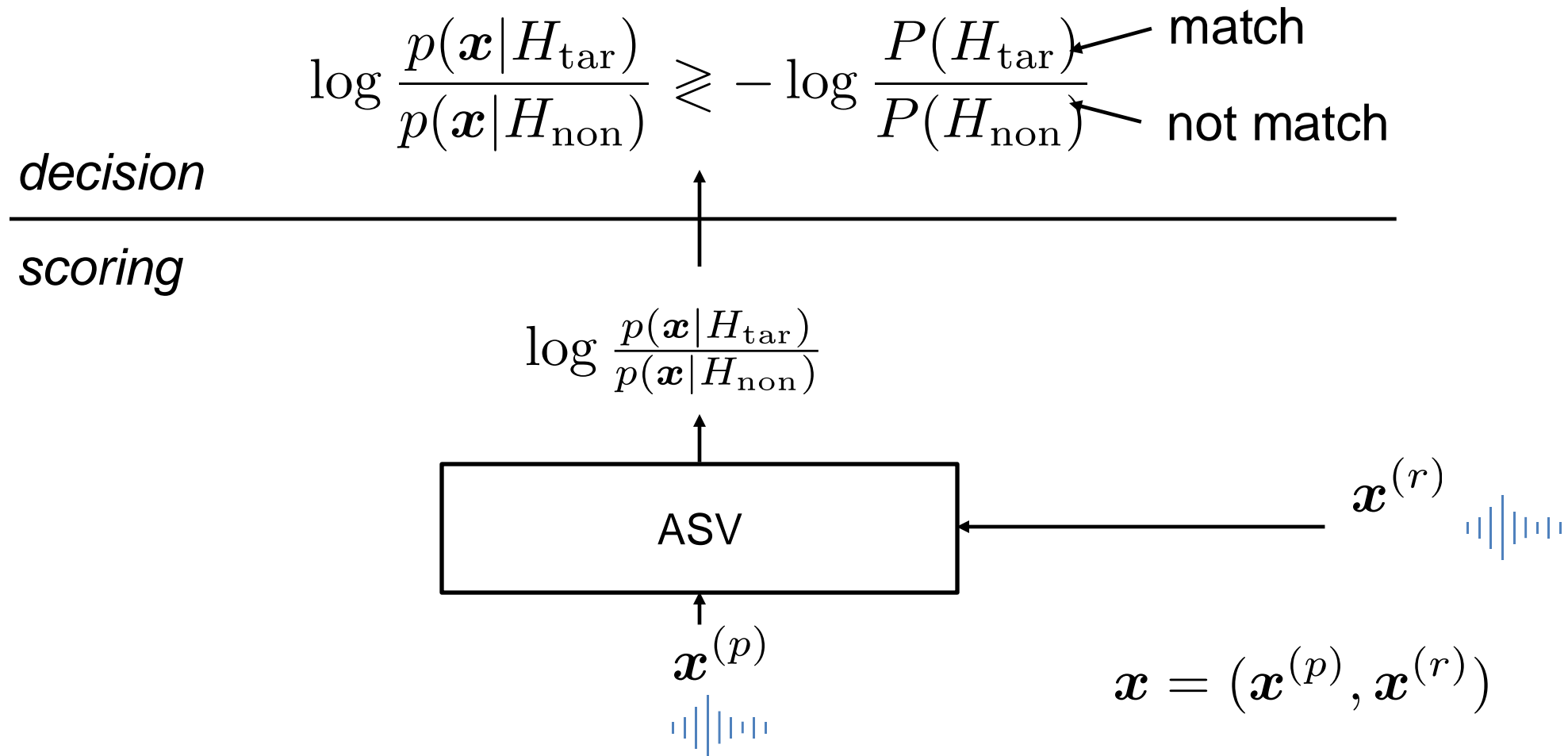
Appendix
theory in details



ASVspooF

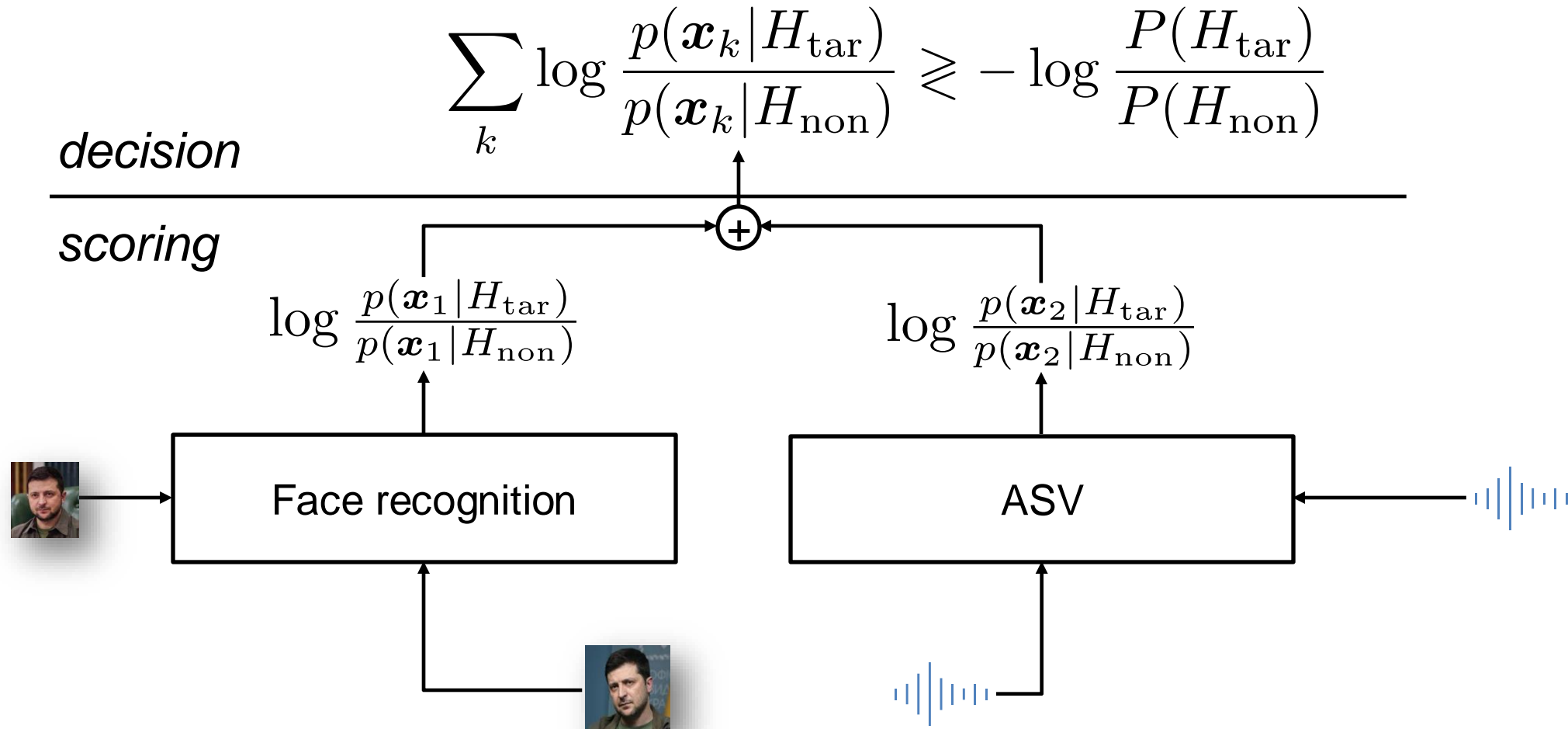
Fusing CM & ASV is special

□ A single ASV



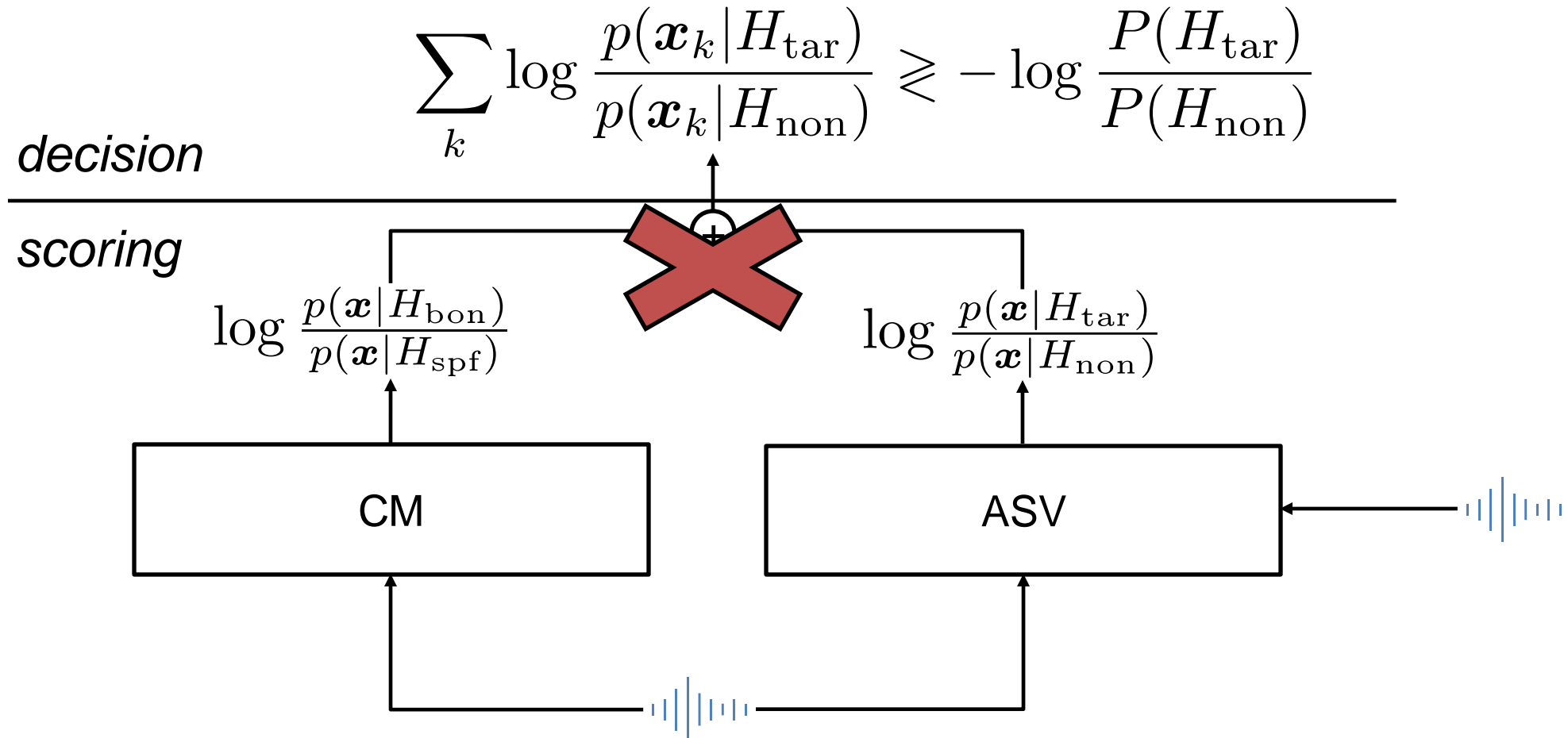
Fusing CM & ASV is special

- Fusing ASV, face recognition, and other biometrics



Fusing CM & ASV is special

- CM and ASV are dealing with different hypotheses



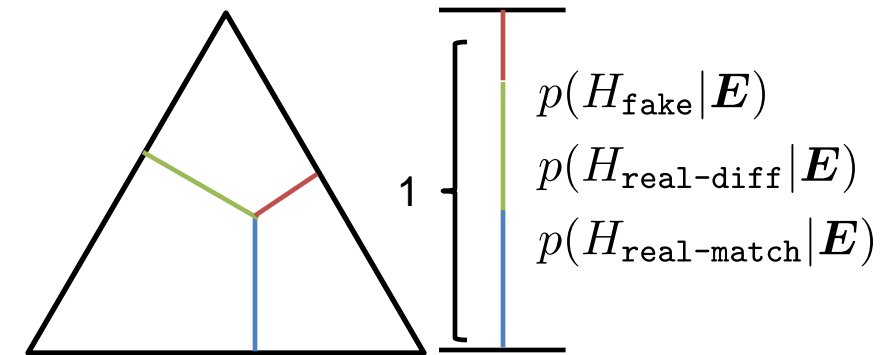
Fusing CM & ASV is special

- We have three classes of data in two separate hypothesis testings

$$\{H_{\text{fake}}, H_{\text{real-diff}}, H_{\text{real-match}}\}$$



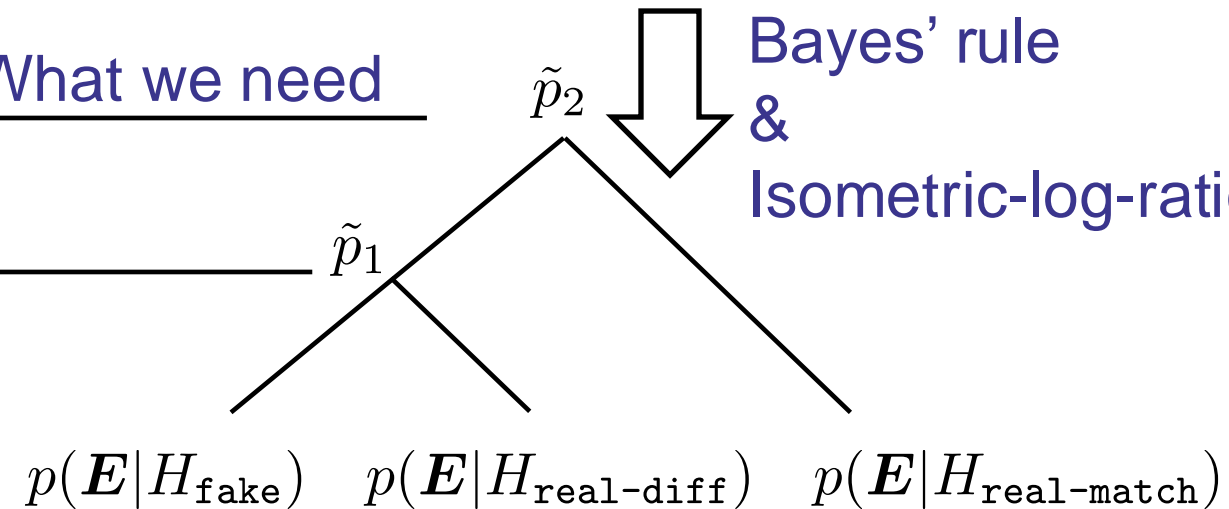
Simplex



Optimal way using ternary hypothesis testing

What we need

Bayes' rule
&
Isometric-log-ratio



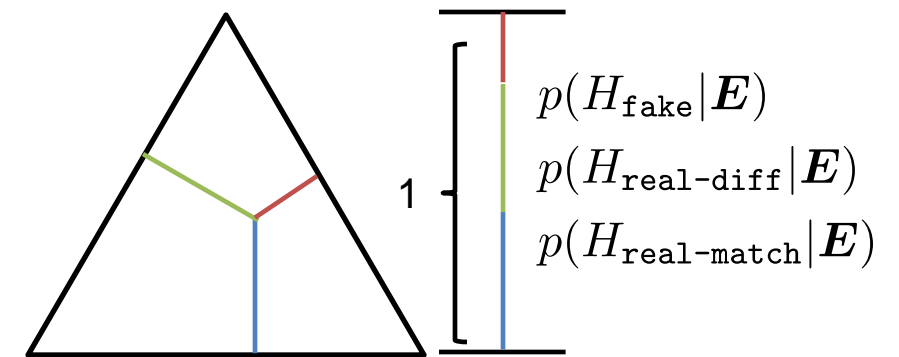
Fusing CM & ASV is special

- We have three classes of data in two separate hypothesis testings

$\{H_{\text{fake}}, H_{\text{real-diff}}, H_{\text{real-match}}\}$



→
Simplex



$$\tilde{p}_2 = \frac{1}{\sqrt{6}} \left[\log \frac{p(\mathbf{E}|H_{\text{real-match}})}{p(\mathbf{E}|H_{\text{fake}})} + \log \frac{p(\mathbf{E}|H_{\text{real-match}})}{p(\mathbf{E}|H_{\text{real-diff}})} \right]$$

Bayes' rule
&
Isometric-log-ratio



log likelihood ratio



log likelihood ratio

