

Extremal Perturbations

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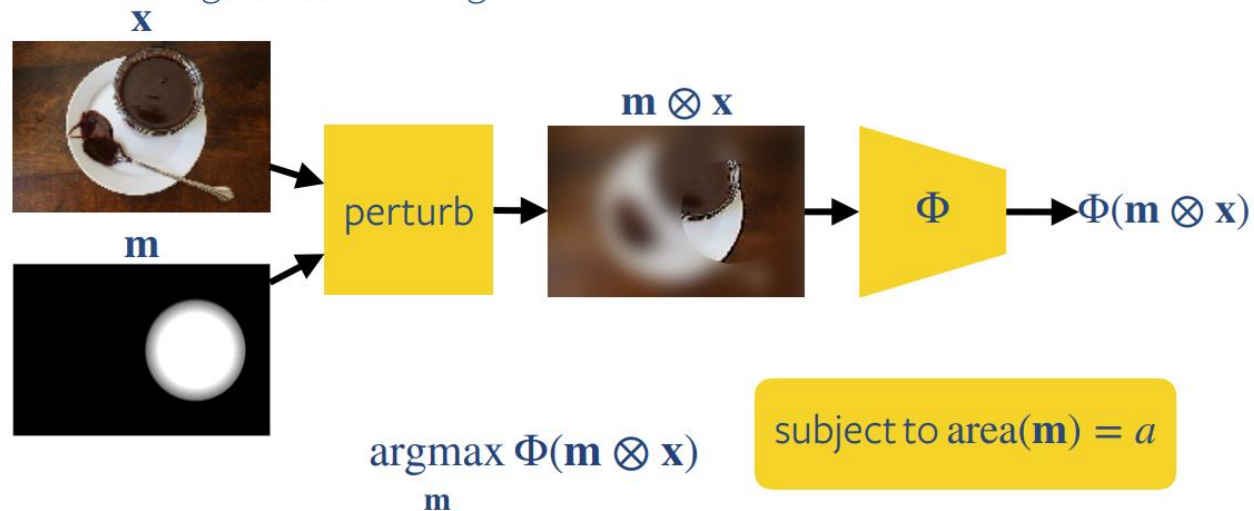
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Review

- What is Extremal Perturbations?

$$a^* = \min\{a : \Phi(\mathbf{m}_a \otimes \mathbf{x}) \geq \Phi_0\}.$$

We optimize the mask \mathbf{m} to maximize the response of the network Φ on the blurred image $\mathbf{m} \otimes \mathbf{x}$ for a given area a :



- R. Fong, M. Patrick and A. Vedaldi, "Understanding Deep Networks via Extremal Perturbations and Smooth Masks," 2019 IEEE/CVF International Conference on Computer Vision (ICCV), 2019, pp. 2950-2958, doi: 10.1109/ICCV.2019.00304.

Review

$$m_a = \operatorname{argmax}_{m \in \mathcal{M}} \Phi(m \otimes x) - \lambda R_a(m).$$

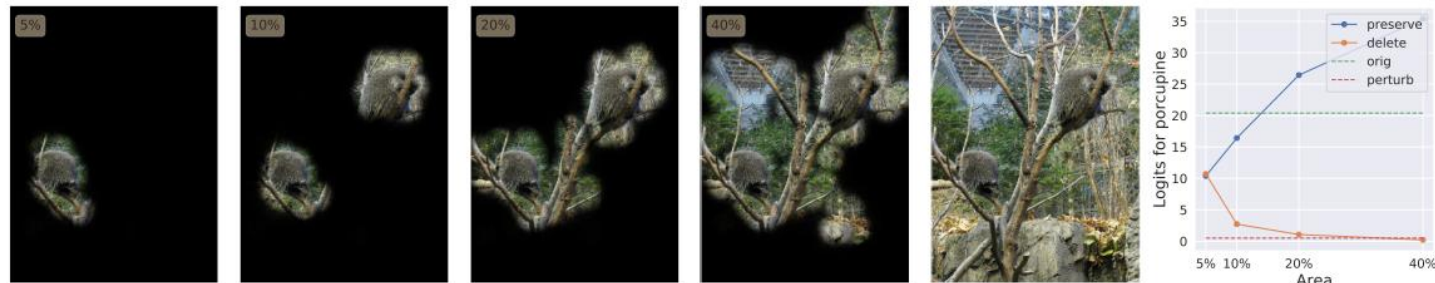


Figure 3: **Extremal perturbations and monotonic effects.** Left: “porcupine” masks computed for several areas a (a in box). Right: $\Phi(m_a \otimes x)$ (preservation; blue) and $\Phi((1 - m_a) \otimes x)$ (deletion; orange) plotted as a function of a . At $a \approx 15\%$ the preserved region scores *higher* than preserving the entire image (green). At $a \approx 20\%$, perturbing the complementary region scores *similarly* to fully perturbing the entire image (red).

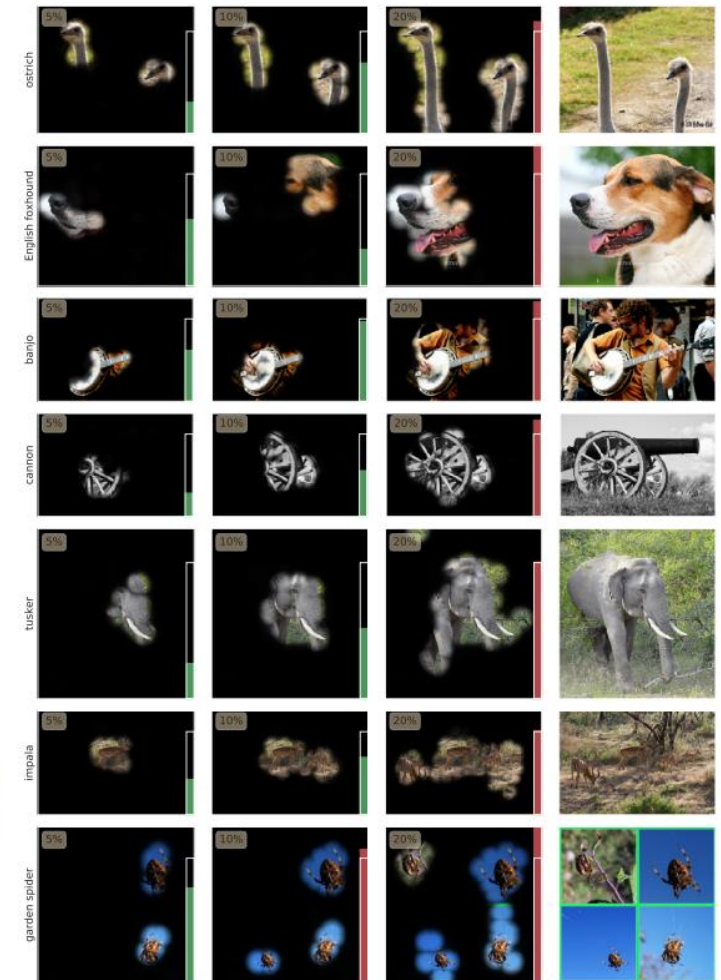


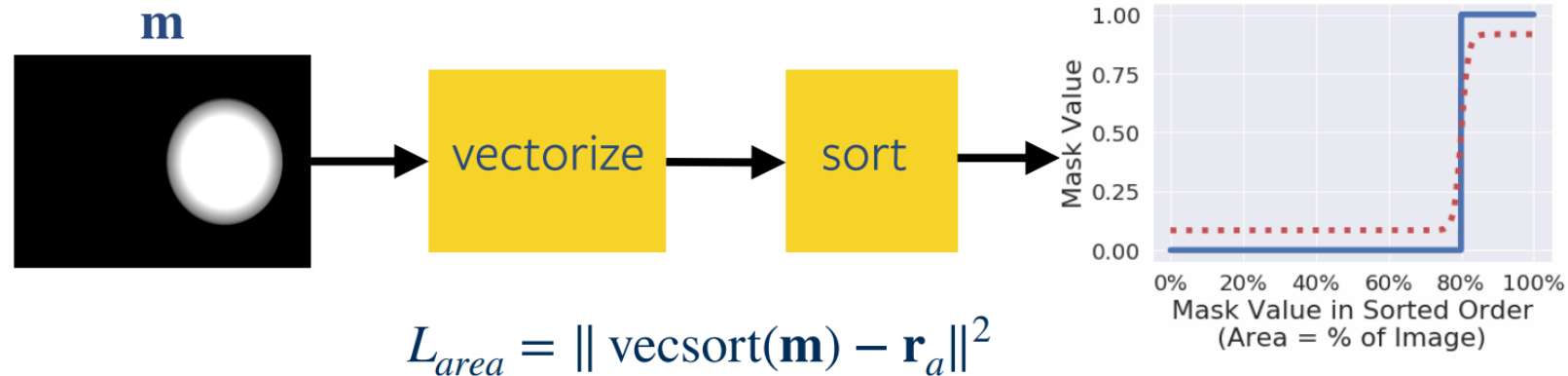
Figure 5: **Area growth.** Although each mask is learned independently, these plots highlight what the network considers to be most discriminative and complete. The bar graph visualizes $\Phi(m_a \odot x)$ as a normalized fraction of $\Phi_0 = \Phi(x)$ (and saturates after exceeding Φ_0 by 25%).

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Method

Area constraint

Optimizing for a given area size is non-trivial. We do it by sorting the mask values and comparing the result to the desired 0-1 distribution \mathbf{r}_a :



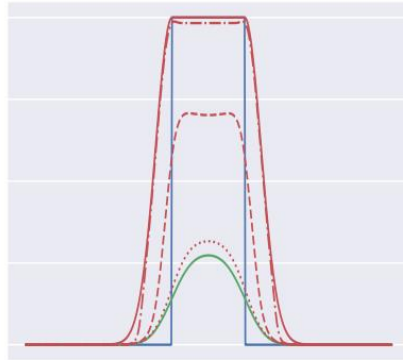
Algorithm

Pick area a and perform SGD to optimize:

$$\underset{\mathbf{m}}{\operatorname{argmax}} \Phi(\text{smoothconv}(\mathbf{m}) \otimes \mathbf{x}) - \lambda \|\text{vecsort}(\text{smoothconv}(\mathbf{m})) - \mathbf{r}_a\|^2$$

Method

Smooth mask



— $m(v)$: mask

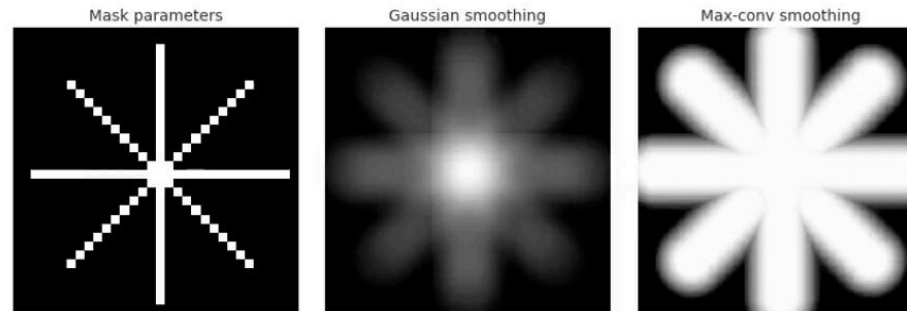
— $\text{conv}(u; m; k) = \frac{1}{Z} \sum_{v \in \Omega} k(u - v)m(v)$

— $\text{maxconv}(u; m; k) = \max_{v \in \Omega} k(u - v)m(v)$

... $\text{smoothconv}(u; m; k; T) = \text{smax}_{v \in \Omega; T} k(u - v)m(v)$

$$\text{smax}_{u \in \Omega; T} f(u) = \frac{\sum_u f(u) \exp(f(u)/T)}{\sum_u \exp(f(u)/T)}$$

Right: comparison between original mask (L), mask after conv (M), and maxconv (R).

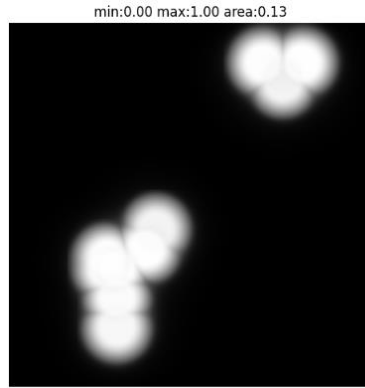


Reproduction

input image



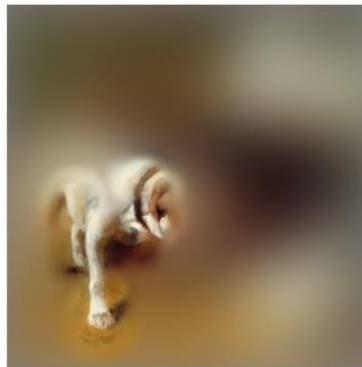
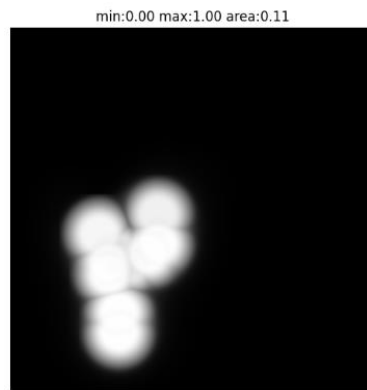
target: dog target area: 0.12



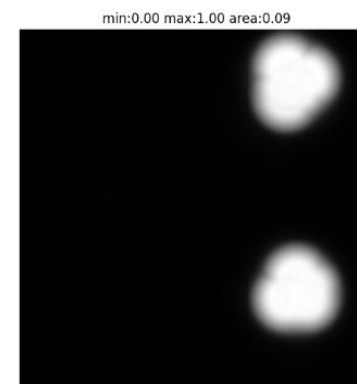
target: cat target area: 0.05



target: dog target area: 0.10

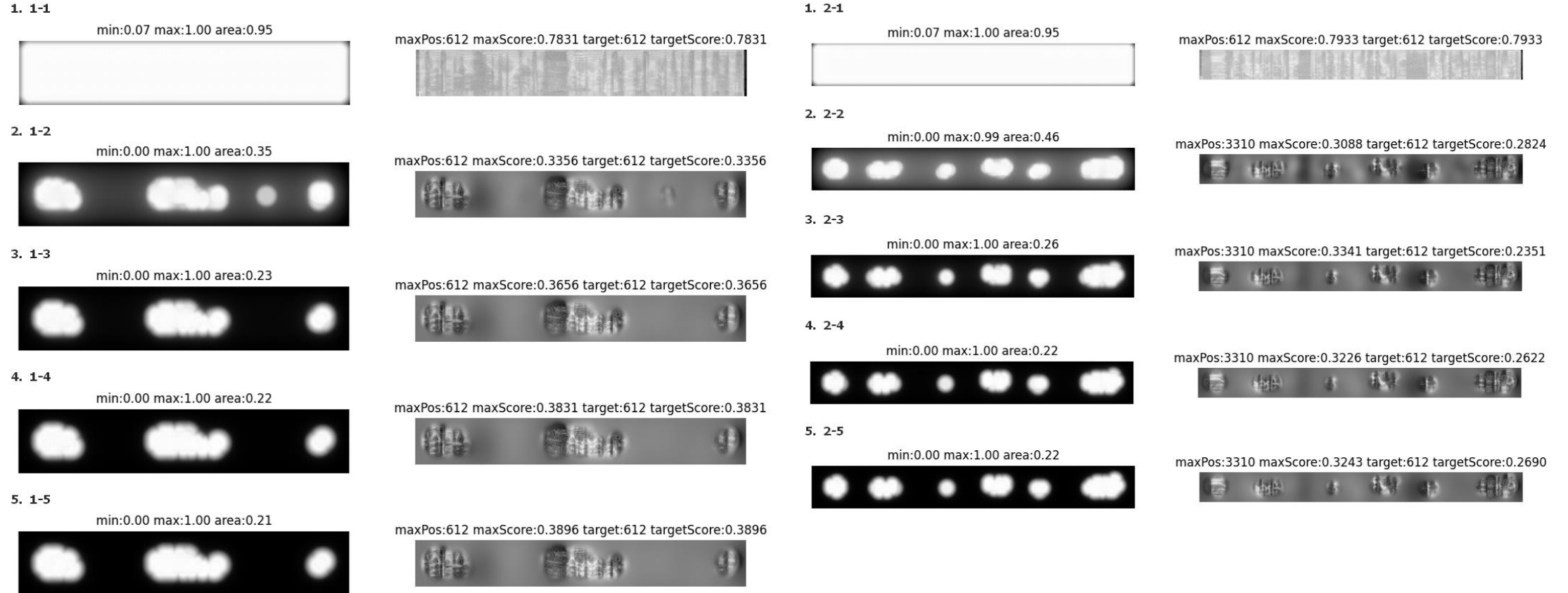


target: cat target area: 0.08



Apply to Speaker Recognition

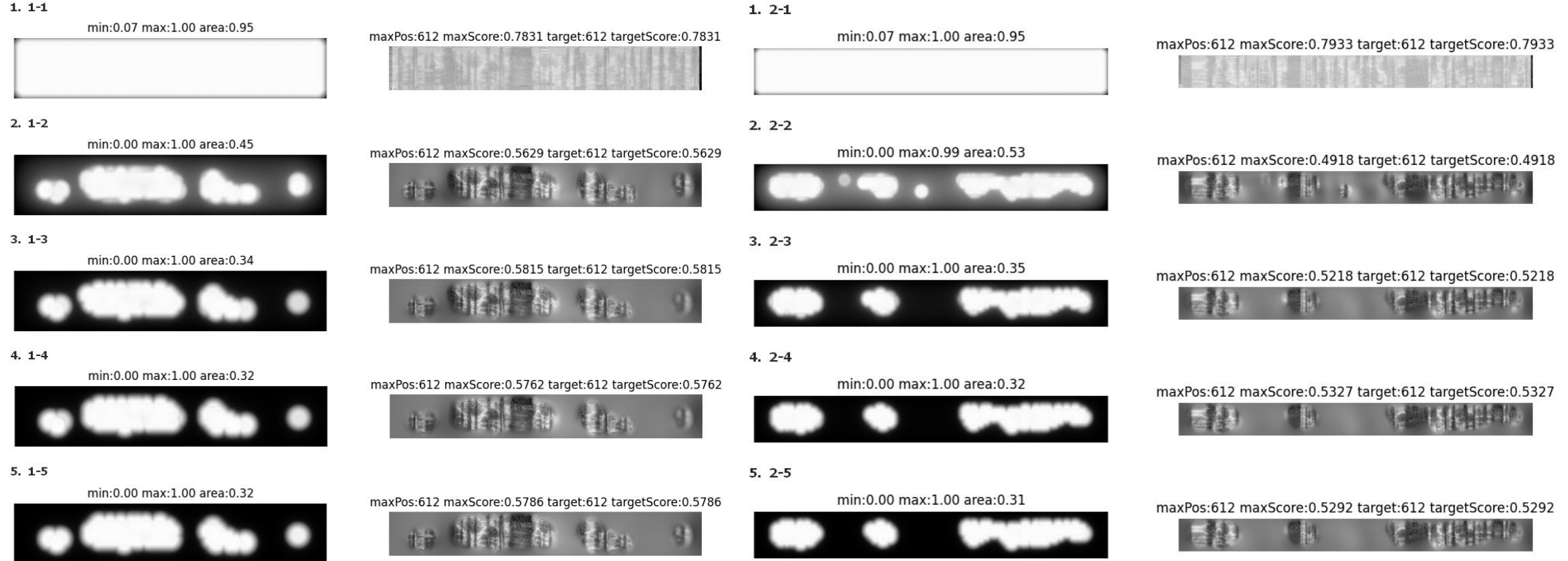
- Single Speaker (target area: 0.20)



- Li, P., Li, L., Hamdulla, A., & Wang, D. (2022). Reliable Visualization for Deep Speaker Recognition. arXiv preprint arXiv:2204.03852.

Apply to Speaker Recognition

- Single Speaker (target area: 0.30)



Some thoughts

- Is it right?
- Why did the score drop so much?

Apply to Speaker Recognition

- Multi Speaker (target area: 0.20)

multi-a-b-a

1. 1-input

maxPos:488 maxScore:0.6438 target:612 targetScore:0.6234



2. 1-mask

min:0.00 max:1.00 area:0.22



3. 1-perturbation

maxPos:612 maxScore:0.3565 target:612 targetScore:0.3565



multi-b-a-b

1. 1-input

maxPos:612 maxScore:0.5269 target:612 targetScore:0.5269



2. 1-mask

min:0.00 max:1.00 area:0.22



3. 1-perturbation

maxPos:5705 maxScore:0.3114 target:612 targetScore:0.2124



Some thoughts

- Hypothesis:
 - There are some commonalities between different speakers.
 - The mask is coarse-grained, while the speaker's common information is relatively discrete, and the personality information is relatively continuous.

Apply to Speaker Recognition

- Single speaker combined noise, silent section (target area: 0.10)

1. 1-input

maxPos:3669 maxScore:0.3384 target:0 targetScore:0.3254



2. 1-mask

min:0.00 max:1.00 area:0.12



3. 1-perturbation

maxPos:1738 maxScore:0.2889 target:0 targetScore:-0.0359



1. 3-input

maxPos:0 maxScore:0.4950 target:0 targetScore:0.4950



2. 3-mask

min:0.00 max:1.00 area:0.12



3. 3-perturbation

maxPos:123 maxScore:0.3394 target:0 targetScore:0.1062



1. 2-input

maxPos:0 maxScore:0.5162 target:0 targetScore:0.5162



2. 2-mask

min:0.00 max:1.00 area:0.11



3. 2-perturbation

maxPos:4339 maxScore:0.3112 target:0 targetScore:-0.0160



Apply to Speaker Recognition

- Single speaker mixed noise, silent section (target area: 0.05)

1. 1-input

maxPos:3669 maxScore:0.3384 target:0 targetScore:0.3254



2. 1-mask

min:0.00 max:1.00 area:0.06



3. 1-perturbation

maxPos:1738 maxScore:0.2767 target:0 targetScore:-0.0329



1. 3-input

maxPos:0 maxScore:0.4950 target:0 targetScore:0.4950



2. 3-mask

min:0.00 max:1.00 area:0.06



3. 3-perturbation

maxPos:4339 maxScore:0.2862 target:0 targetScore:-0.0439



1. 2-input

maxPos:0 maxScore:0.5162 target:0 targetScore:0.5162



2. 2-mask

min:0.00 max:1.00 area:0.05



3. 2-perturbation

maxPos:4339 maxScore:0.3306 target:0 targetScore:-0.0525



Some thoughts

- The key areas are all within the speaker's time domain segment.
- The blurred part affects the score.
- Initially, the hypothesis is verified.

Next work

- Adjust granularity
- Quantitative experiments for hypothesis

Thanks!