Estimating Confidence of Speech Spoofing Countermeasure

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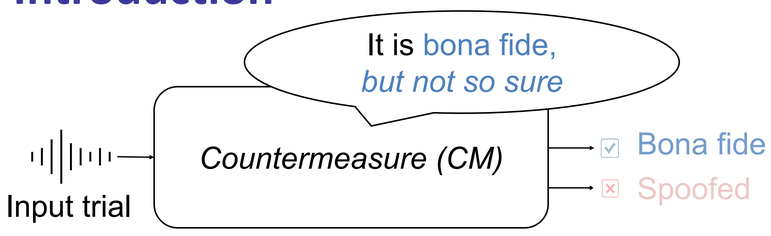
Introduction



Existing CMs usually do not produce confidence.

CM confidence may be informative:

- abstention: avoid risky decisions for low-confidence trials
- active learning: annotate them and add to training data [1]

How to estimate confidence scores? Any benefit?

Methods to estimate confidence *c*

Let $\{P_0, P_1\}$ be prob. of {*spoofed* and *bona fide*}.

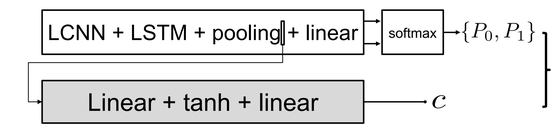
Let $\{l_0, l_1\}$ be logits of softmax output layer.

I Max-prob. estimator[2]: $c = \max\{P_0, P_1\}$

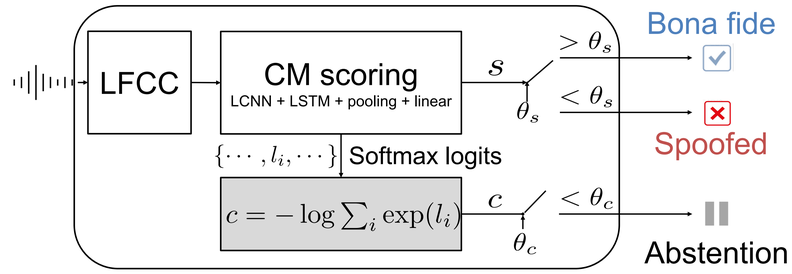
II Negative energy[3]: $c = -\log \sum_i \exp(l_i)$

III Min negative Mahalanobis dis. [4]

IV Jointly trained DNN conf. estimator[5]:



V Independent DNN conf. estimator (require labels)



	Score range	Trainable?
Max prob.	$c \in [0.5, 1)$	No
Energy score	$c \in \mathbb{R}$	No
Neg. M-dist.	$c \in (-\infty, 0)$	Trained after CM
Conf. branch	$c \in (0, 1)$	Jointly trained with CM
Supervised	$c \in (0, 1)$	Separately trained

Experiments

Model config

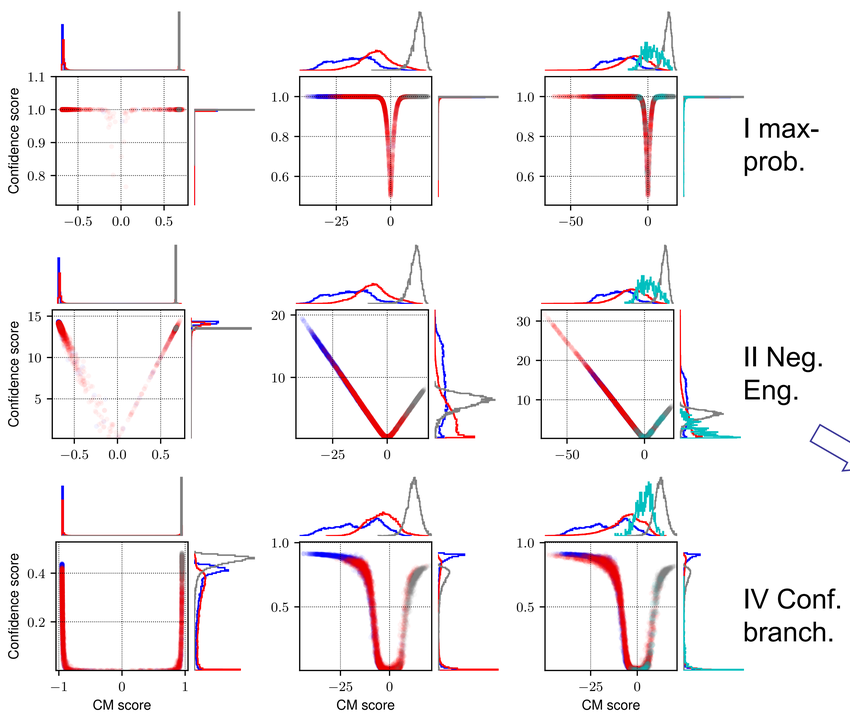
- LFCC, LCNN + LSTM + pooling + linear[6]
- Either additive margin (AM) or vanilla plain softmax

Database & protocols

- *unknown* trials should receive low conf., i.e., they do not match with training data in terms of channel, language, …
- *known* trials should receive high conf..
- Two test sets to simulate different testing scenarios.
- Let's focus only on T1 training set, which is is the standard ASVspoof 2019 LA training set.

		Known trials	*Unknown* trials
Train set	T1	LA trn. (2,580 / 22,800)	-
	T2	LA trn. (2,580 / 22,800)	ESPNet (250 / 2,000)
	T3	LA trn. (2,580 / 22,800)	BC19 (100 / 7,625)
Test set	E1	LA test kn. (7,355 / 19,656)	LA test unk. (0 / 44,226)
	E2	LA test kn. (7,355 / 19,656)	VCC (770 / 49,467)

[1] Settles, B. Active Learning Literature Survey. 2009.
[2] Hendrycks D., A Baseline for Detecting Misclassified and Out-of-Distribution Examples in Neural Networks. In *ICLR*. 2017.
[3] Liu, W., et al.. Energy-Based Out-of-Distribution Detection. In *Proc. NIPS*, 33:21464–21475. 2020.
[4] Lee, K., et. al. A Simple Unified Framework for Detecting Out-of-Distribution Samples and Adversarial Attacks. in *NIPS*, 2018.
[5] DeVries, T. & Taylor, G. W. Learning confidence for out-of-distribution detection in neural networks. arXiv1802.04865, 2018
[6] Wang, X. et. al. A comparative study on recent neural spoofing countermeasures for synthetic speech detection. in *Interspeech* 2021



Unknown spoofed and Unknown bona fide should have lower conf. scores.

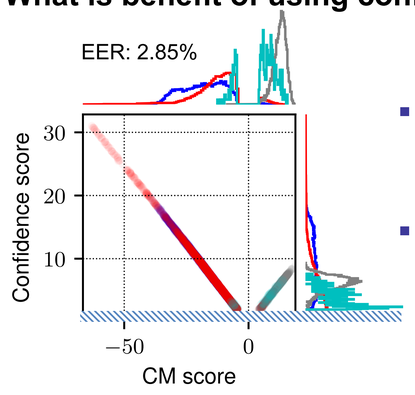
Known spoofed and Known bona fide should have higher conf. scores.

Messages

Can conf. scores be estimated?

- x max-prob. and a few methods
- ✓ Promising: Neg. energy and conf. branch are
- With AM-softmax, no, CM scores follow bi-nomial dist. – the CM is over-confident
- With plain softmax, yes

What is benefit of using confidence scores?



- Avoid making decisions on trials w/ low conf. scores
- Select useful training data w/ low conf. (see arxiv:)

Limitation: unknown unknowns are difficult to detect, for example, unknown bona fide data with low CM scores

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Contact: wangxin@nii.ac.jp, Code: https://github.com/nii-yamagishilab/project-NN-Pytorch-scripts

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