Who is Real Bob? Adversarial Attacks on Speaker Recognition Systems

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Speaker Recognition Systems (SRSs)

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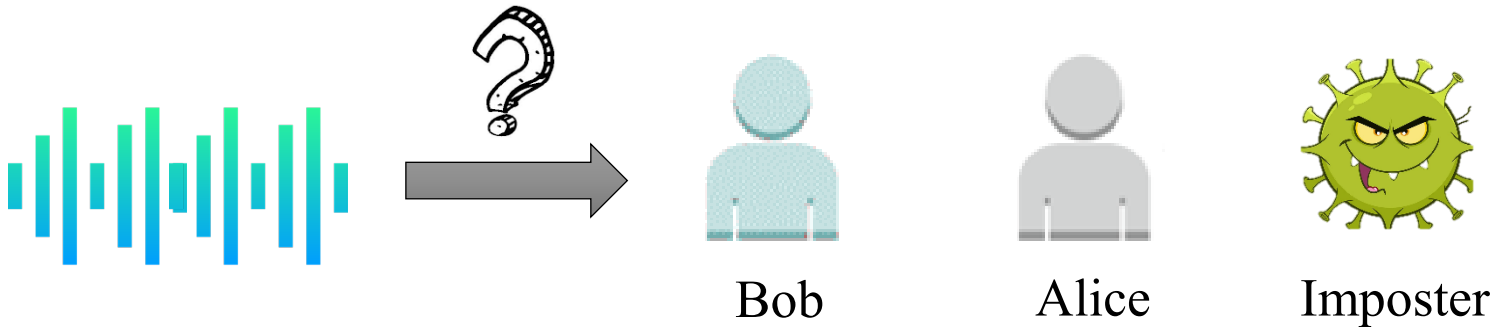

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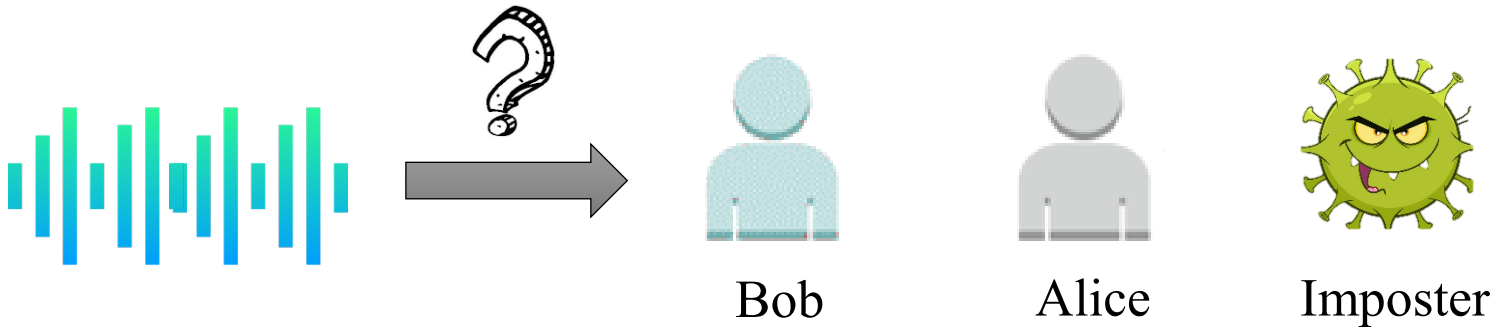
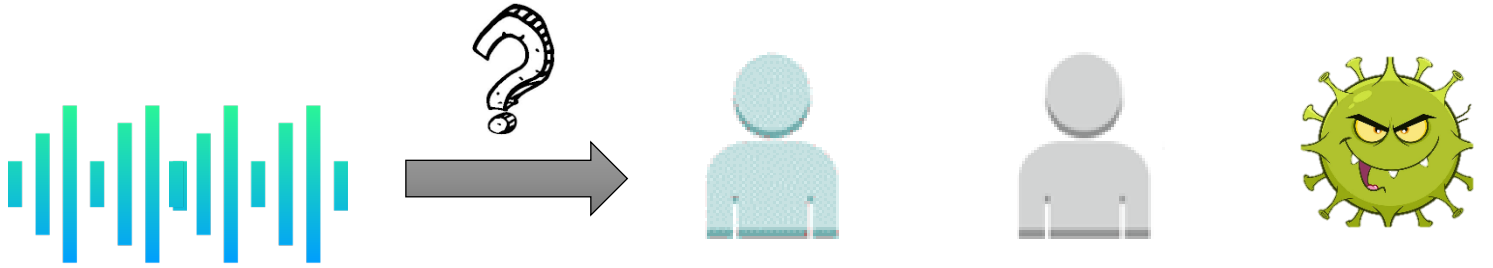


Ubiquitous Application

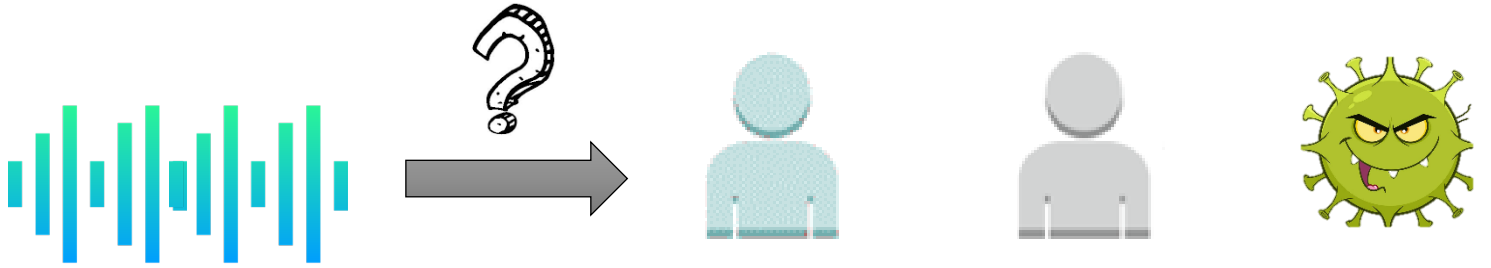
Speaker Recognition Systems (SRSs)



Ubiquitous Application

Voice assistant wake up

Speaker Recognition Systems (SRSs)



Bob Alice Imposter

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Personalized service
on smart home

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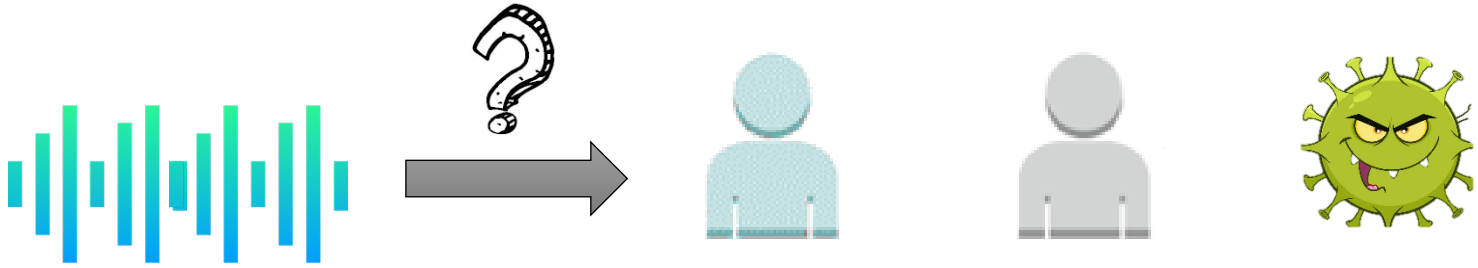

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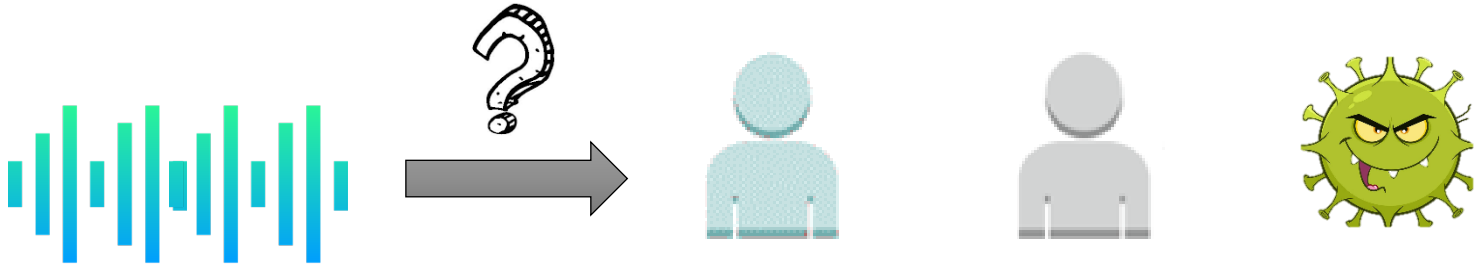

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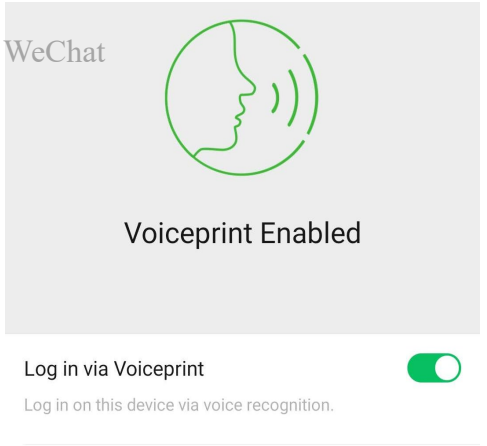

App log in

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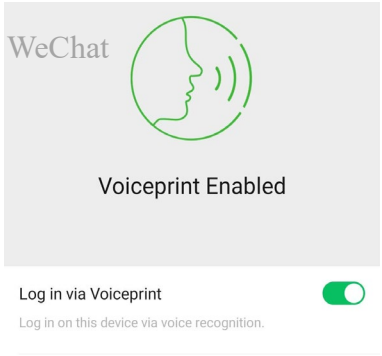

App log in

Safety-critical scenario

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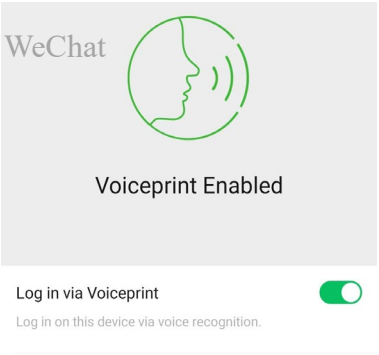

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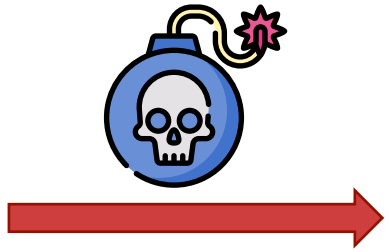

Once broken

Ubiquitous Application

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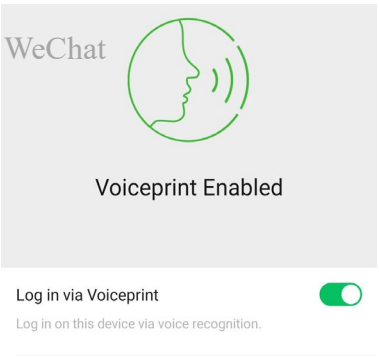

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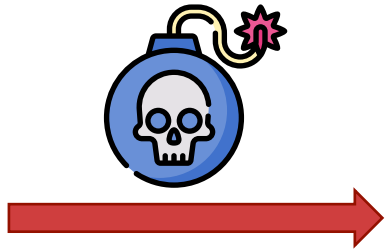

Once broken

property damage

reputation degrade

sensitive information leak

…

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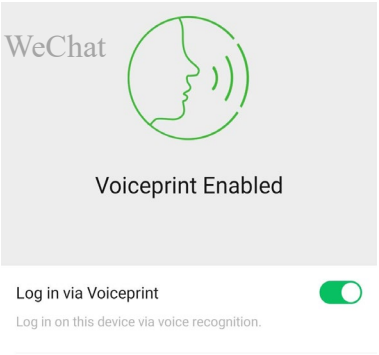

App log in

Security of SRSs!!!

Mainstream implementation of SRSs

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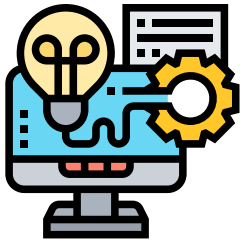
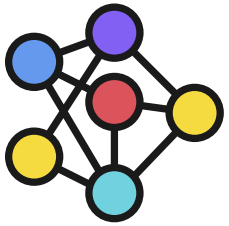


Machine Learning
(ML)



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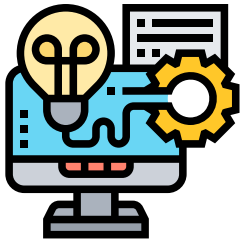

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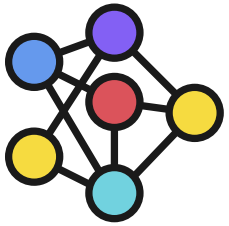

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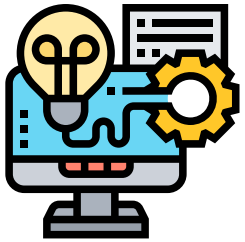

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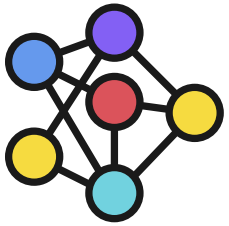

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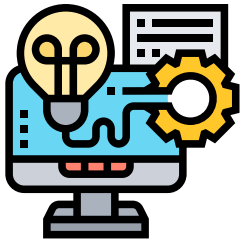

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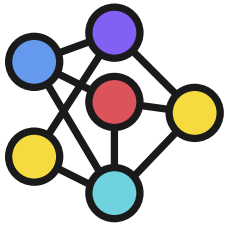

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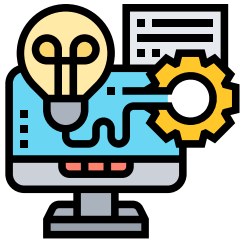
Benign example
Result: Panda
Confidence: 57.7%

Perturbation

Adversarial example
Result: Gibbon
Confidence: 99.3%

Ian Goodfellow et al.

Mainstream implementation of SRSs



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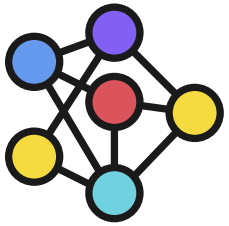

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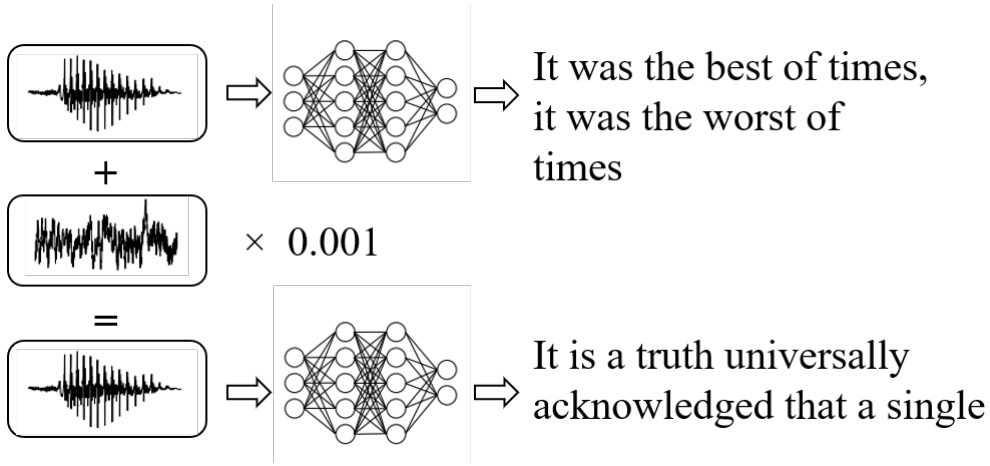

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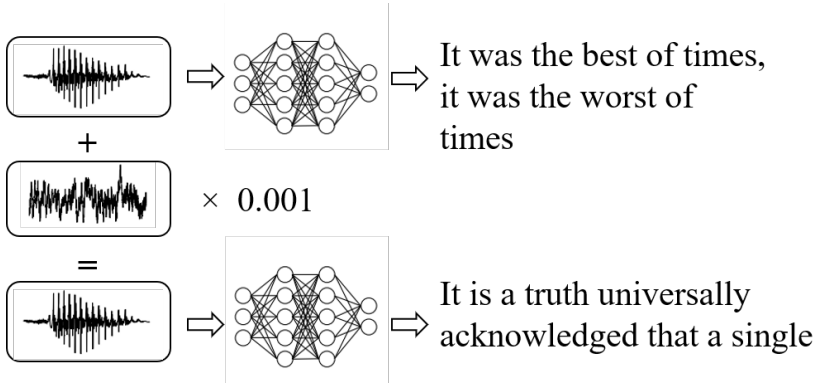

Is adversarial attack practical on SRSs ?

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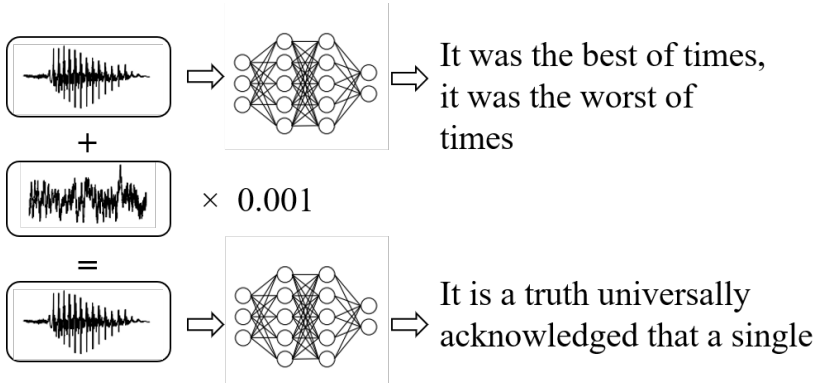


Is adversarial attack practical on SRSs ?

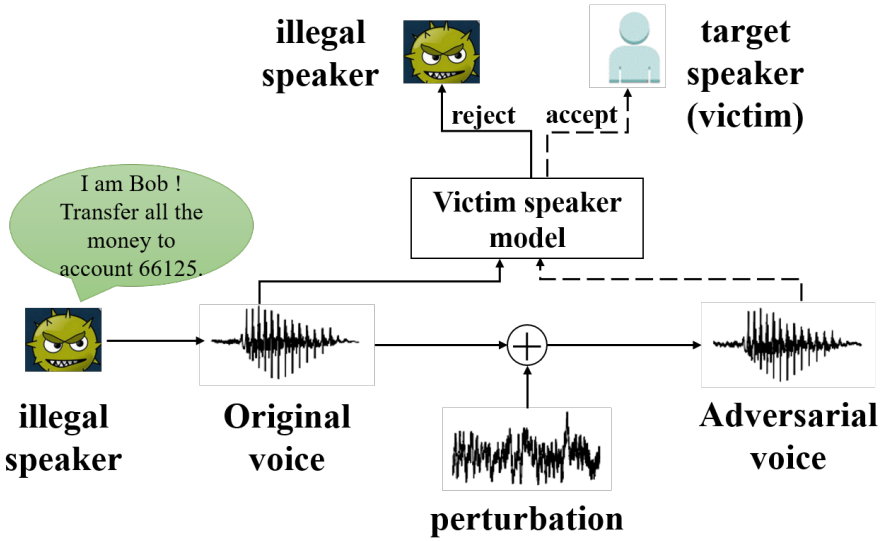
FAKEBOB

- Black-box
- Appliable to general SRS task
- Effective on commercial SRSs
- Effective in over-the-air attack

Threat model

Threat model

- Attacker Goal: pass voice authentication; gain access to privilege



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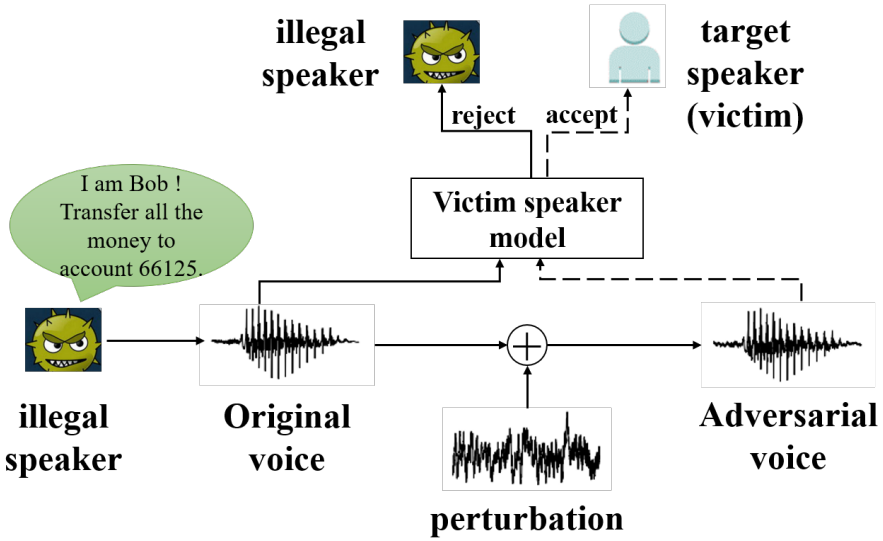

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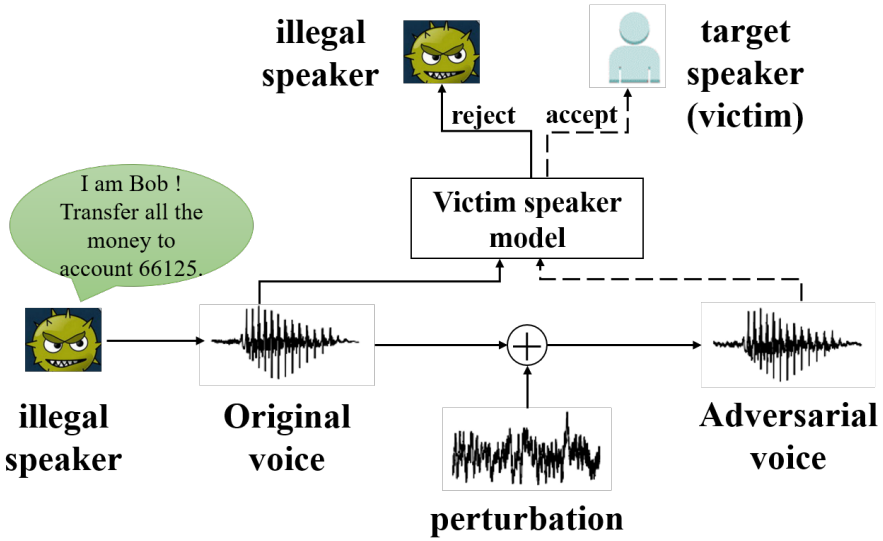
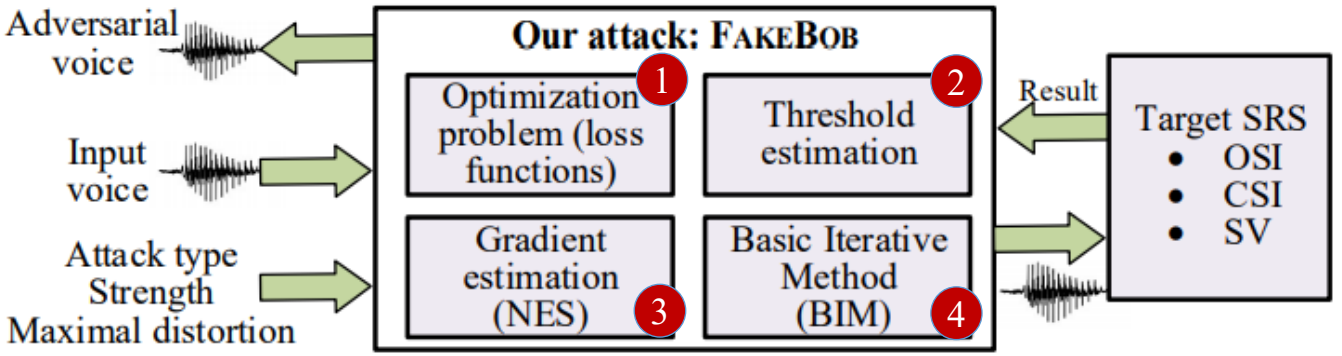


- Attacker Capability: no information about model structure / parameter; limited to query the speak model of the victims

Overview of FAKEBOB



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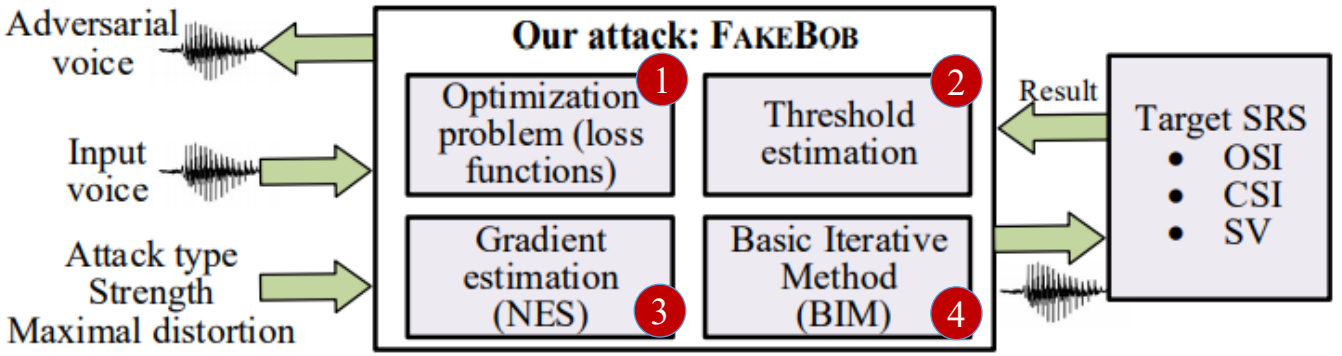

1. Effective **loss function** design.

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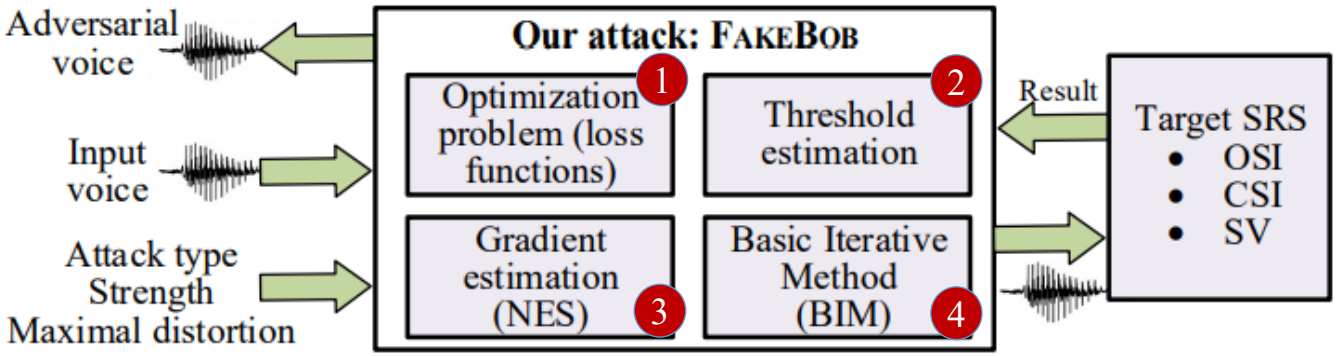

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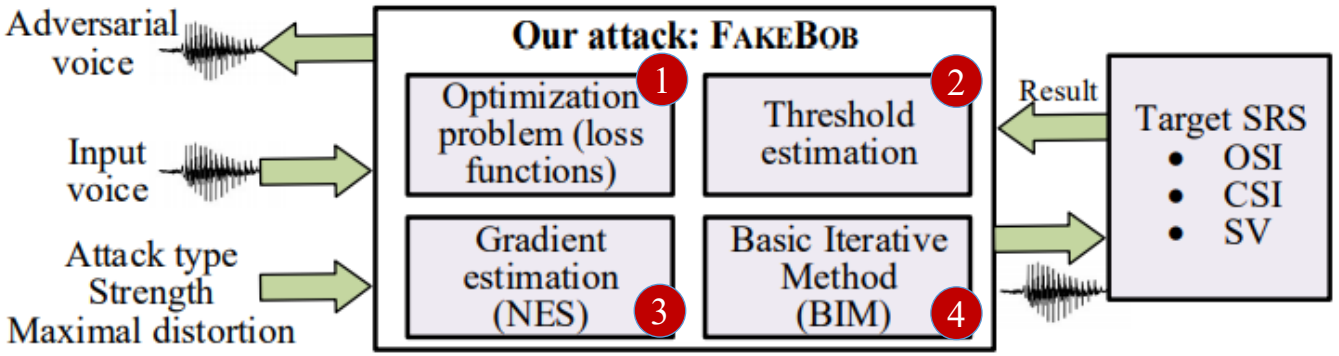

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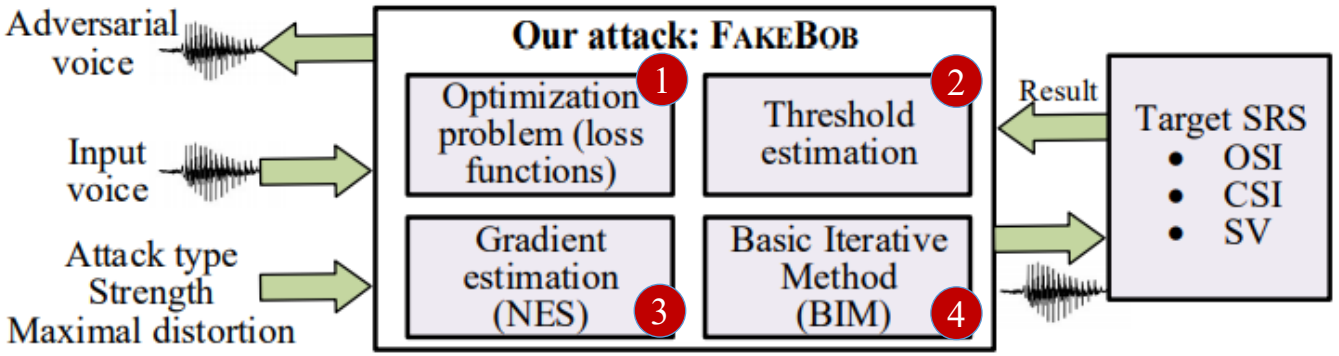

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$$f(x) = \max\{\theta, \max_{i \neq t}[S(x)]_i\} + \kappa - [S(x)]_t$$

Open-set identification (OSI) task

θ: threshold

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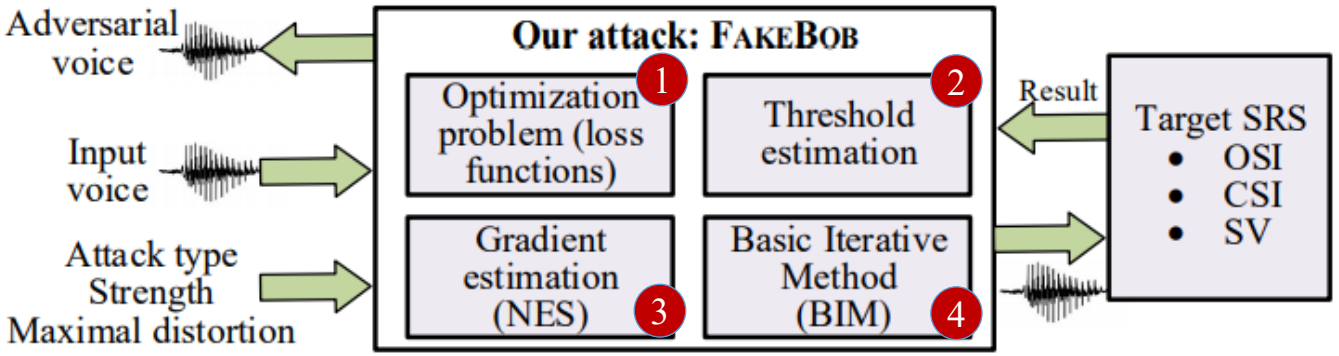

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Tailored for different SRSs **tasks**: CSI, SV, OSI

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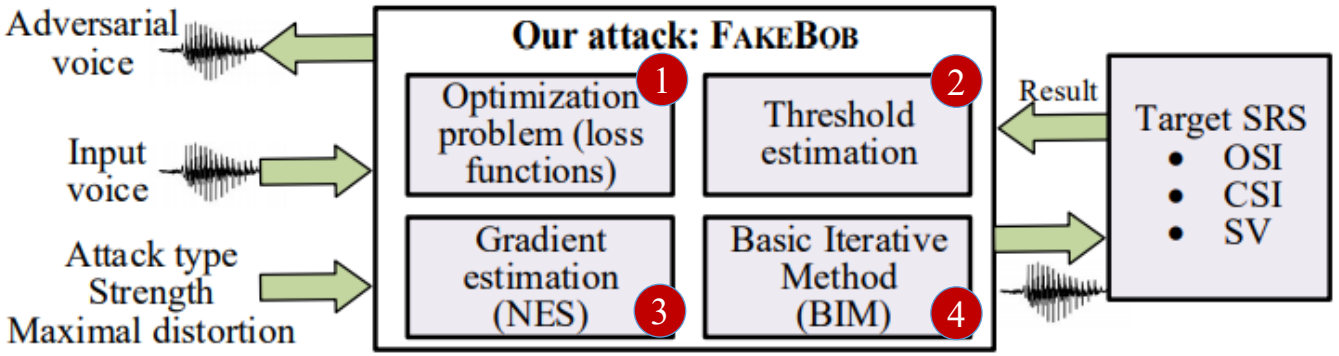

2 **Threshold**: unique in VPR; unknown to attacker

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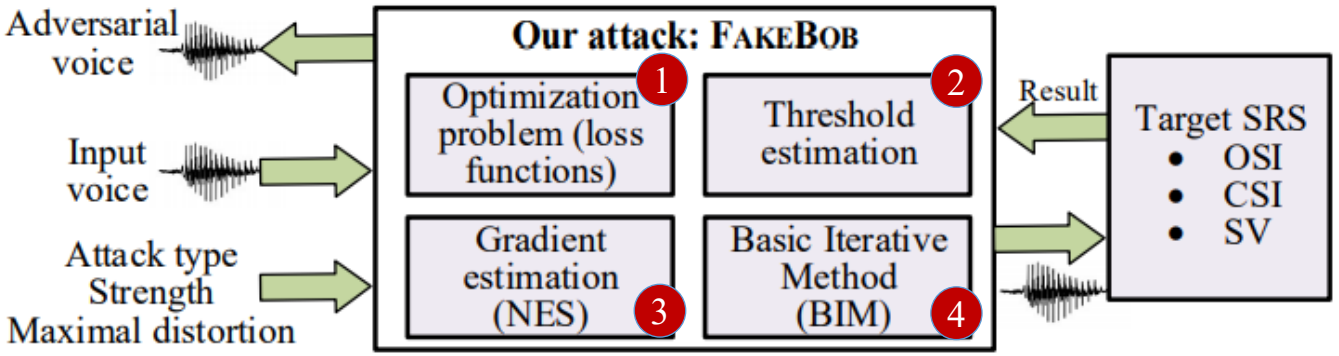

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Novel **threshold estimation** algorithm

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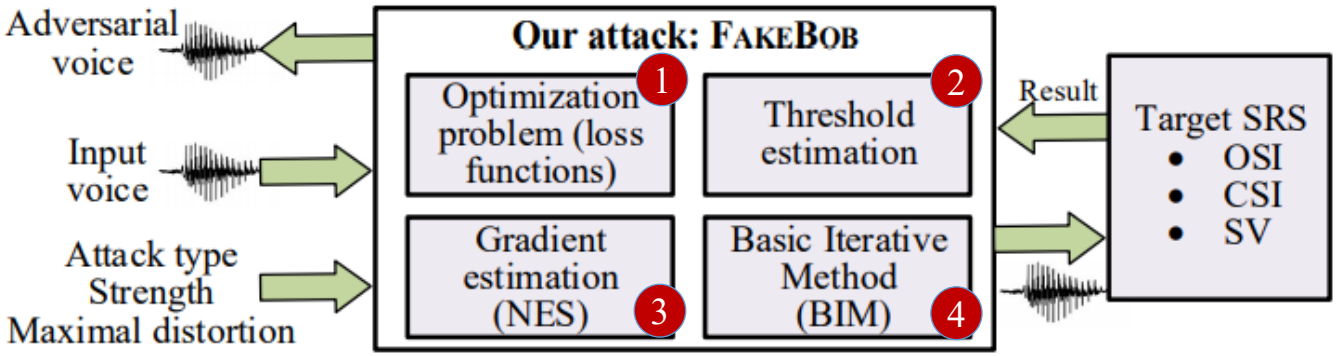

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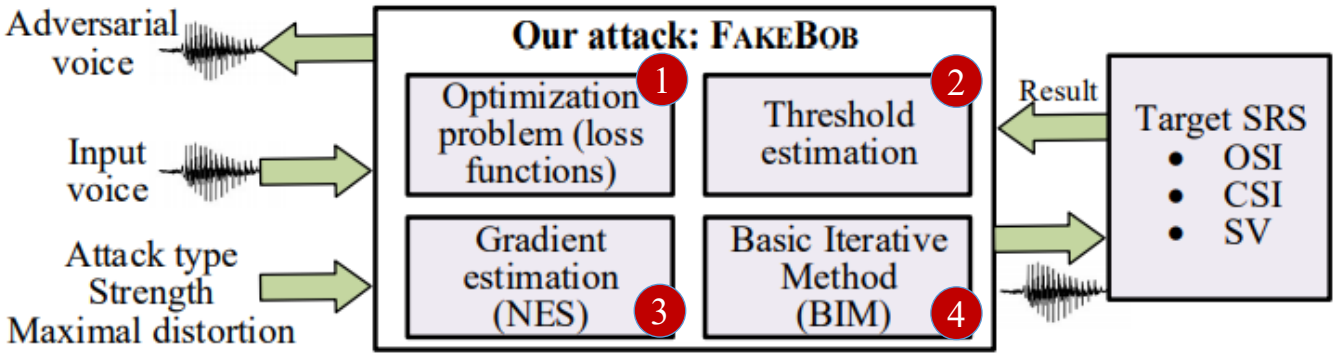

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$$f(x) = \max\{\theta, \max_{i \neq t}[S(x)]_i\} + \kappa - [S(x)]_t \xrightarrow{\hat{\theta} \approx \theta} f(x) = \max\{\hat{\theta}, \max_{i \neq t}[S(x)]_i\} + \kappa - [S(x)]_t$$

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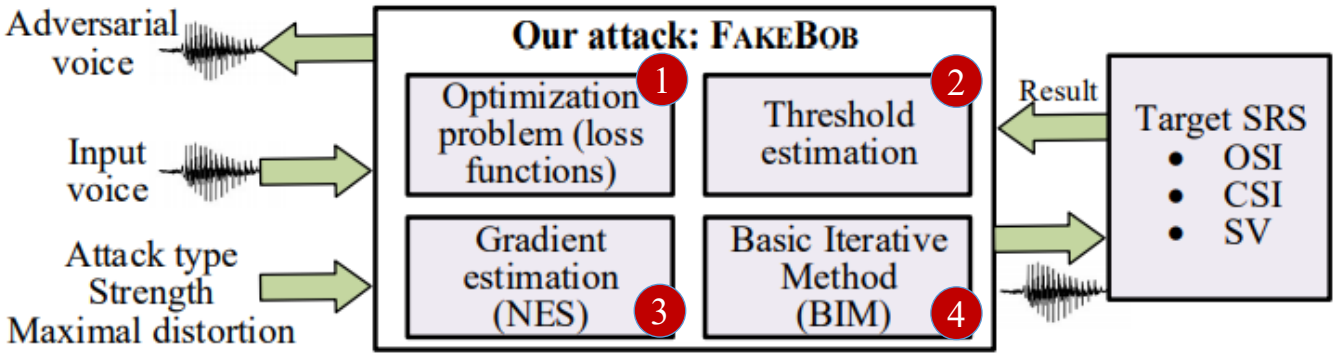

3 NES-based gradient estimation

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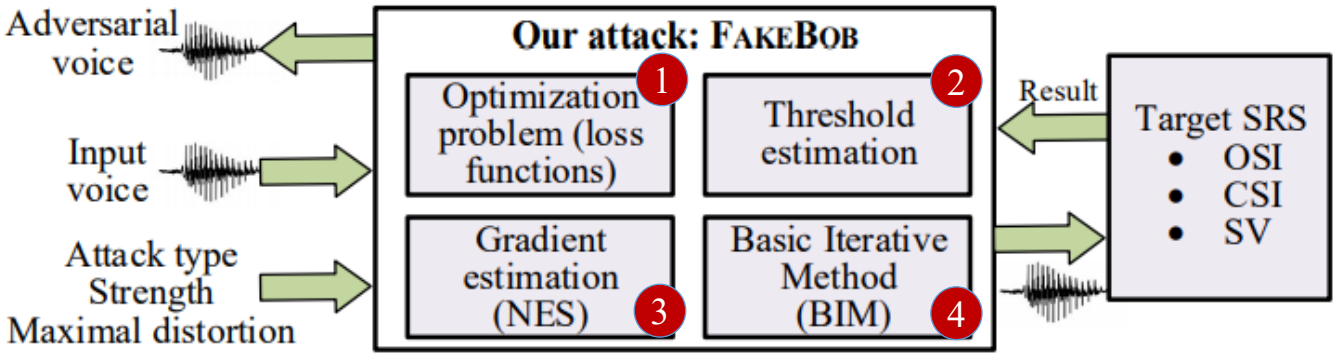

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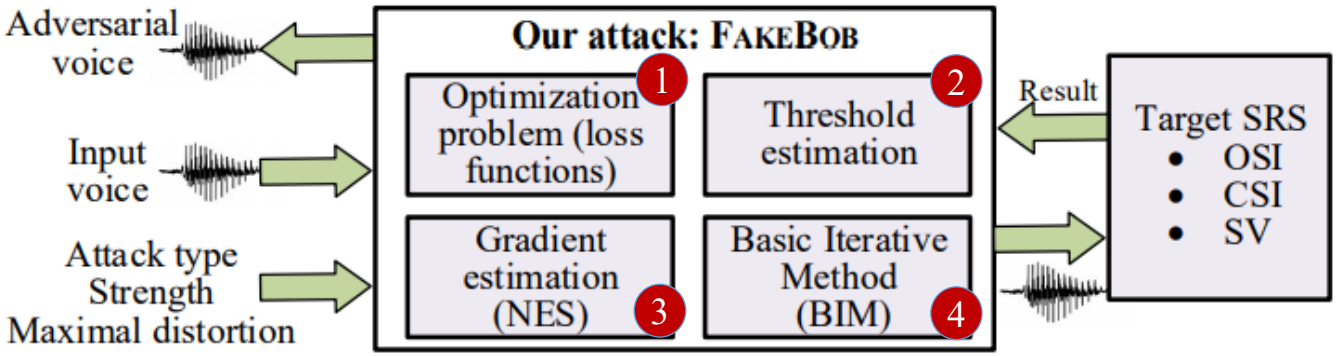
rely on scores and decisions by querying victim speaker model

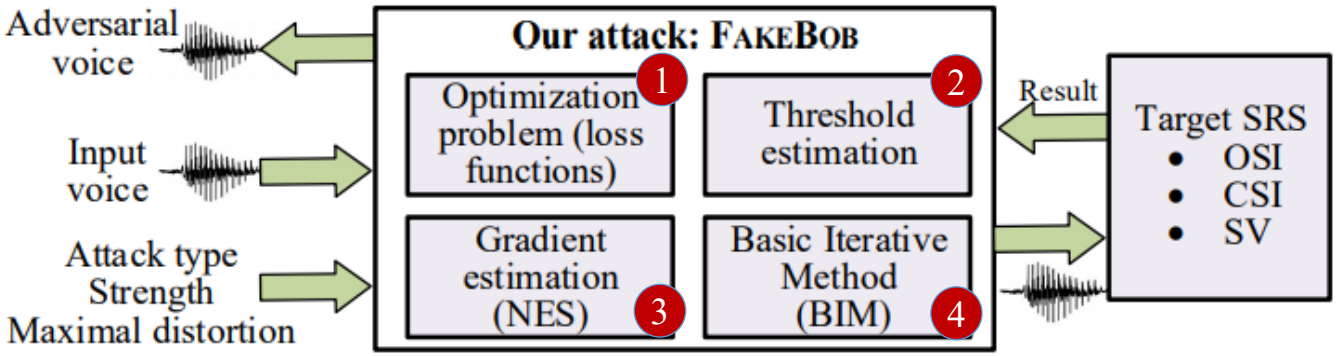
Overview of FAKEBOB



3 NES-based gradient estimation

rely on scores and decisions by querying victim speaker model → Black-box

Overview of FAKEBOB

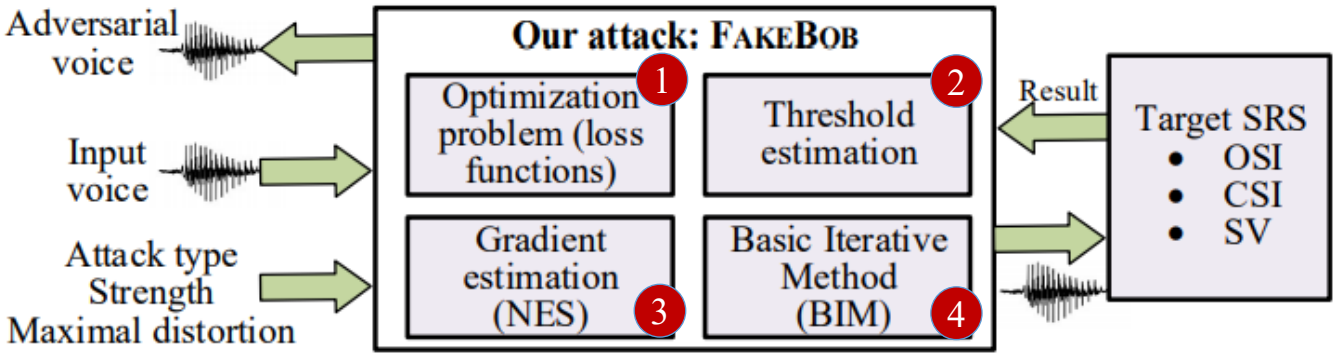


3. NES-based gradient estimation

gradient information

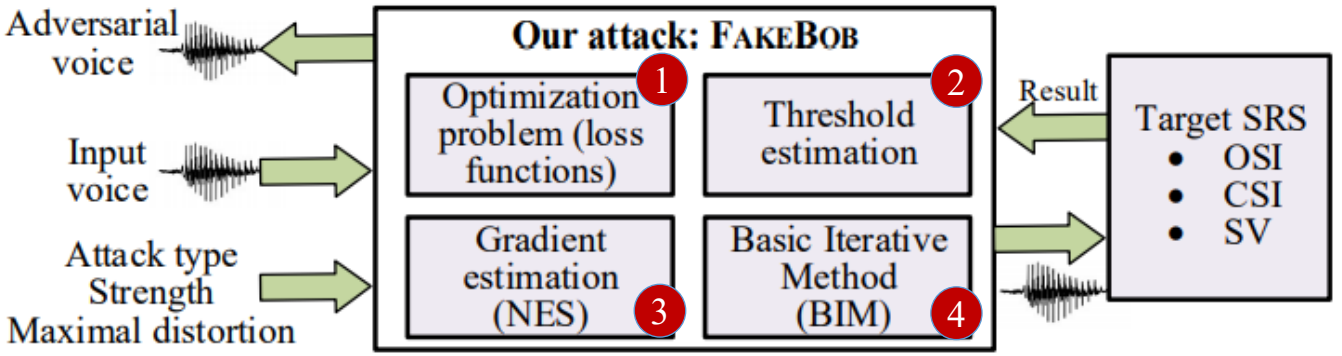
4. Solve the optimization problem by gradient descent

Overview of FAKEBOB



5 Over-the-air attack

Overview of FAKEBOB



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noise in air makes attack ineffective

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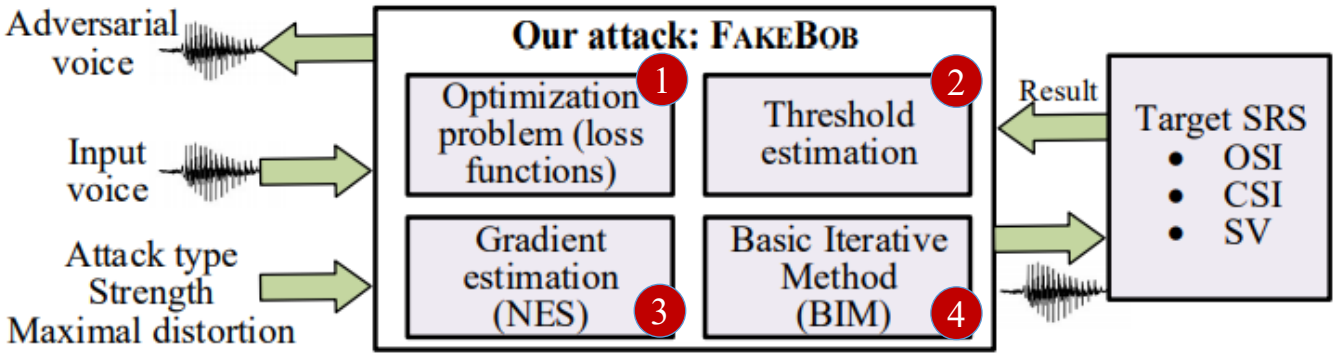

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previous work: noise model

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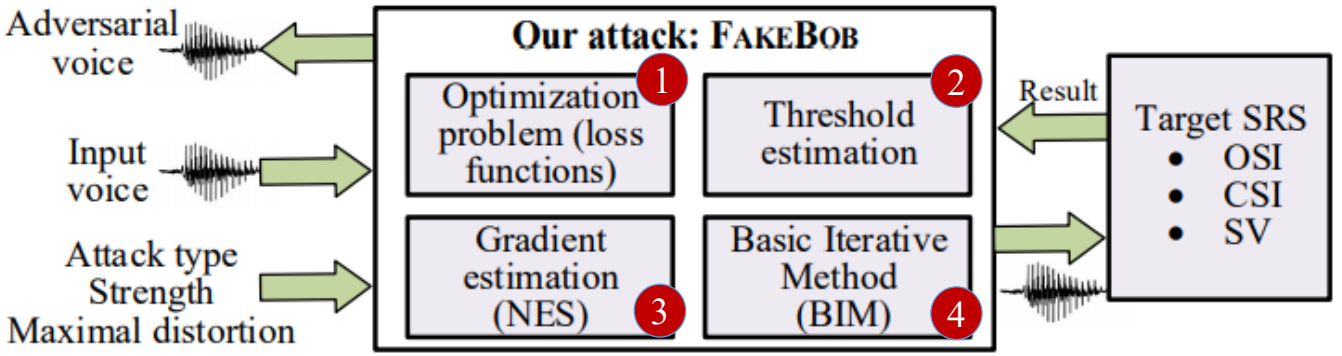

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previous work: noise model → somehow environment- and device- dependent

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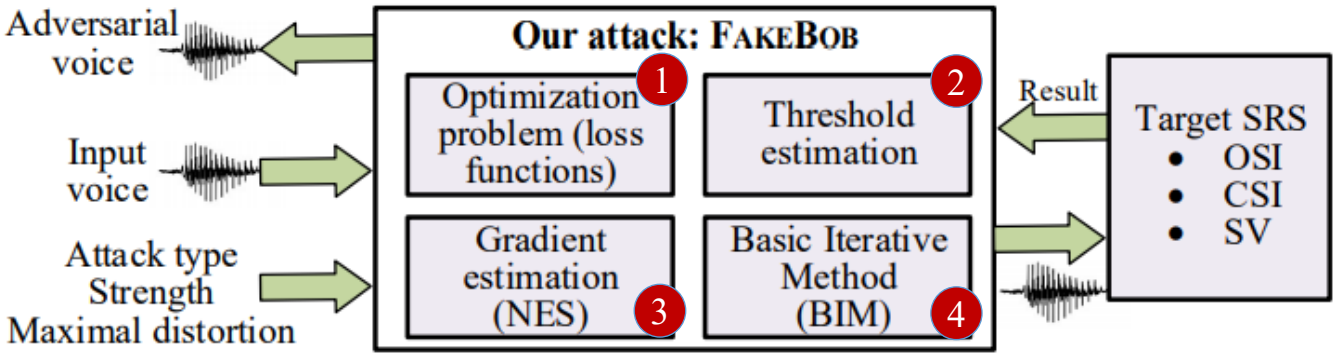

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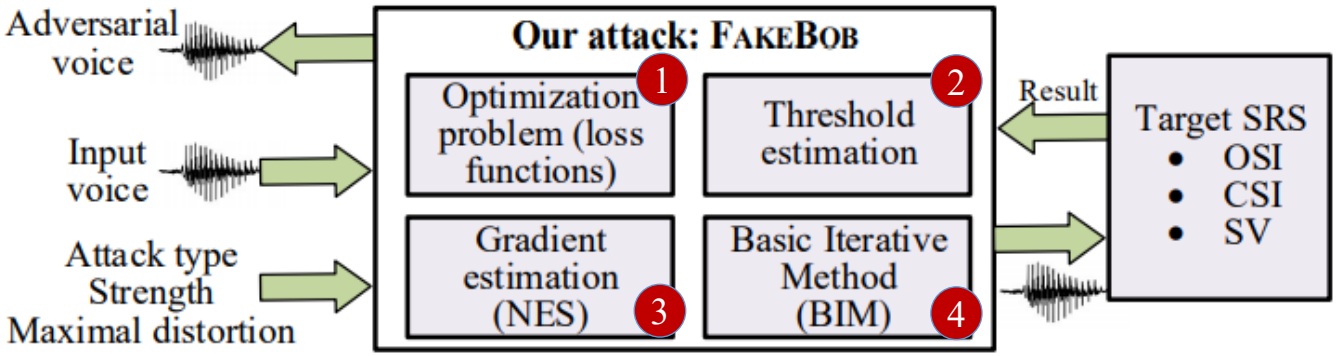

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noise in air makes attack ineffective

previous work: noise model → somehow environment- and device- dependent

ours: improve confidence κ

$$f(x) = \max\{\hat{\theta}, \max_{i \neq t}[S(x)]_i\} + \kappa - [S(x)]_t$$

Experimental result

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- Attack **Open-source** 

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  - ≈ 100% attack success rate (ASR)

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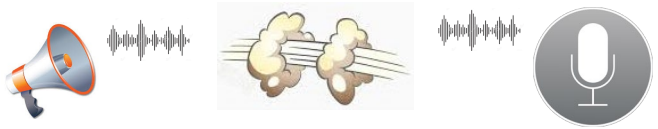
  - **Microsoft Azure:** 26% ASR 

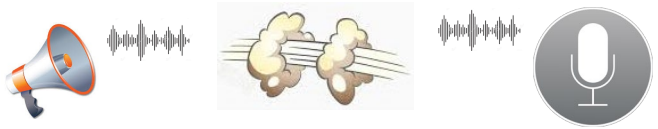
Experimental result

- Over the air Attack



Experimental result

- Over the air Attack

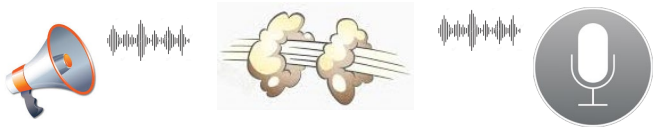


  - different distance between loundspeaker and microphone

Distance (meter)	**0.25**	**0.5**	**1**	**2**	**4**	**8**
ASR (%)	100	100	100	70	40	10

Experimental result

- Over the air Attack



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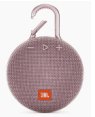
- Different devices (at least 70% ASR)

Loundspeaker:

Laptop



JBL portable speaker

Shinco broadcast equipment

Microphone:

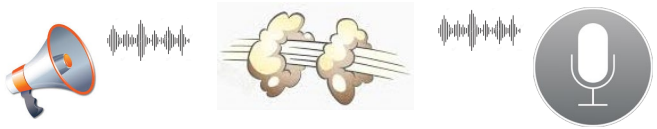
Apple iPhone

OPPO

Device independent

Experimental result

- Over the air Attack



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Distance (meter)	**0.25**	**0.5**	**1**	**2**	**4**	**8**
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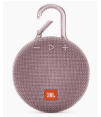
- different acoustic environments
  White / Bus / Restaurant / Music noise
  at least **48%** ASR when noise < 60 dB

Environment independent

- Different devices (at least 70% ASR)

Loundspeaker:

Laptop



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Imperceptibility

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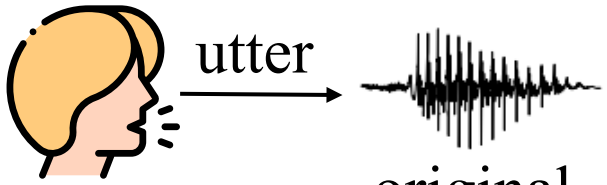
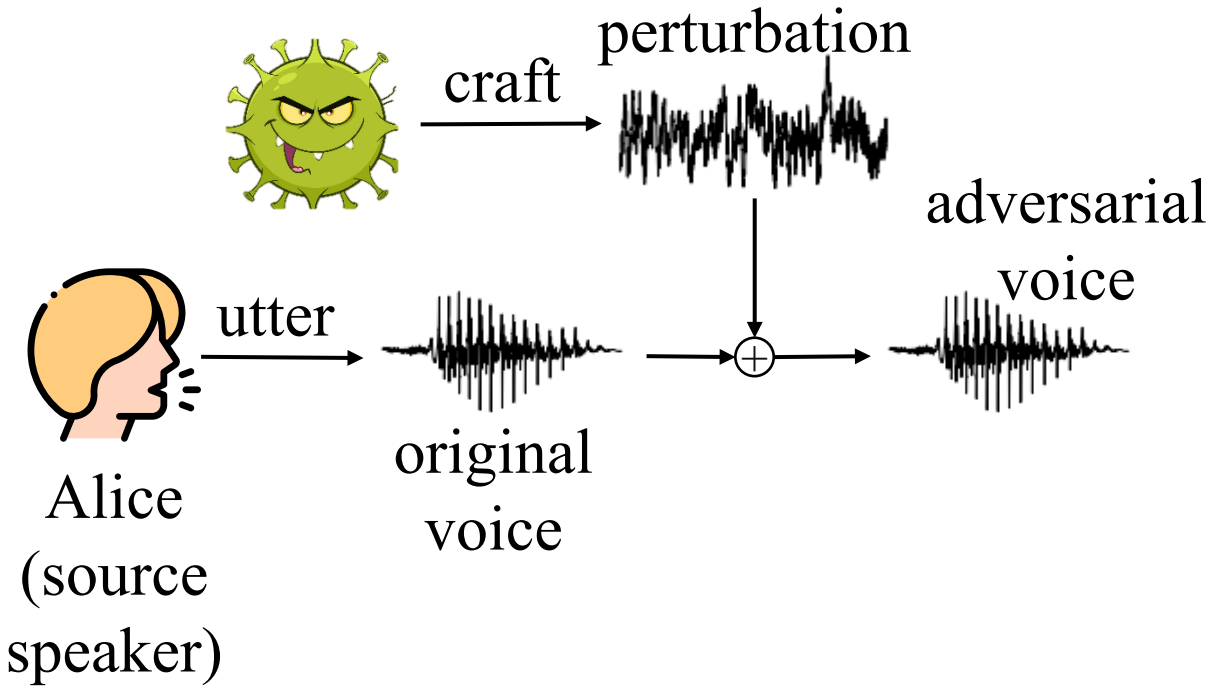


Alice (source speaker)

original voice

Imperceptibility



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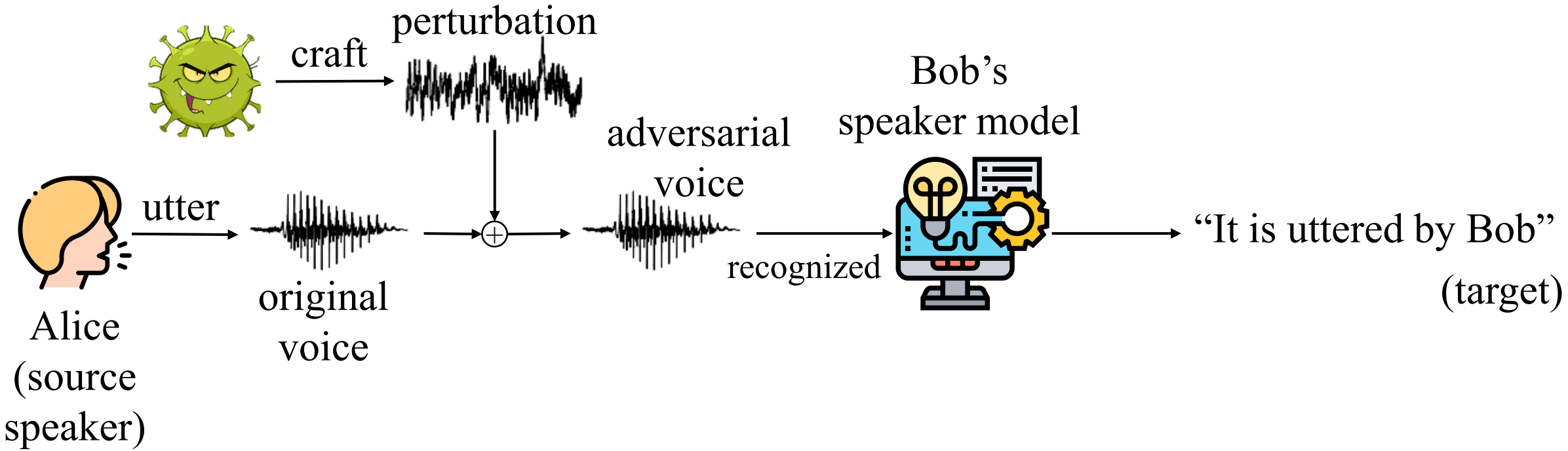

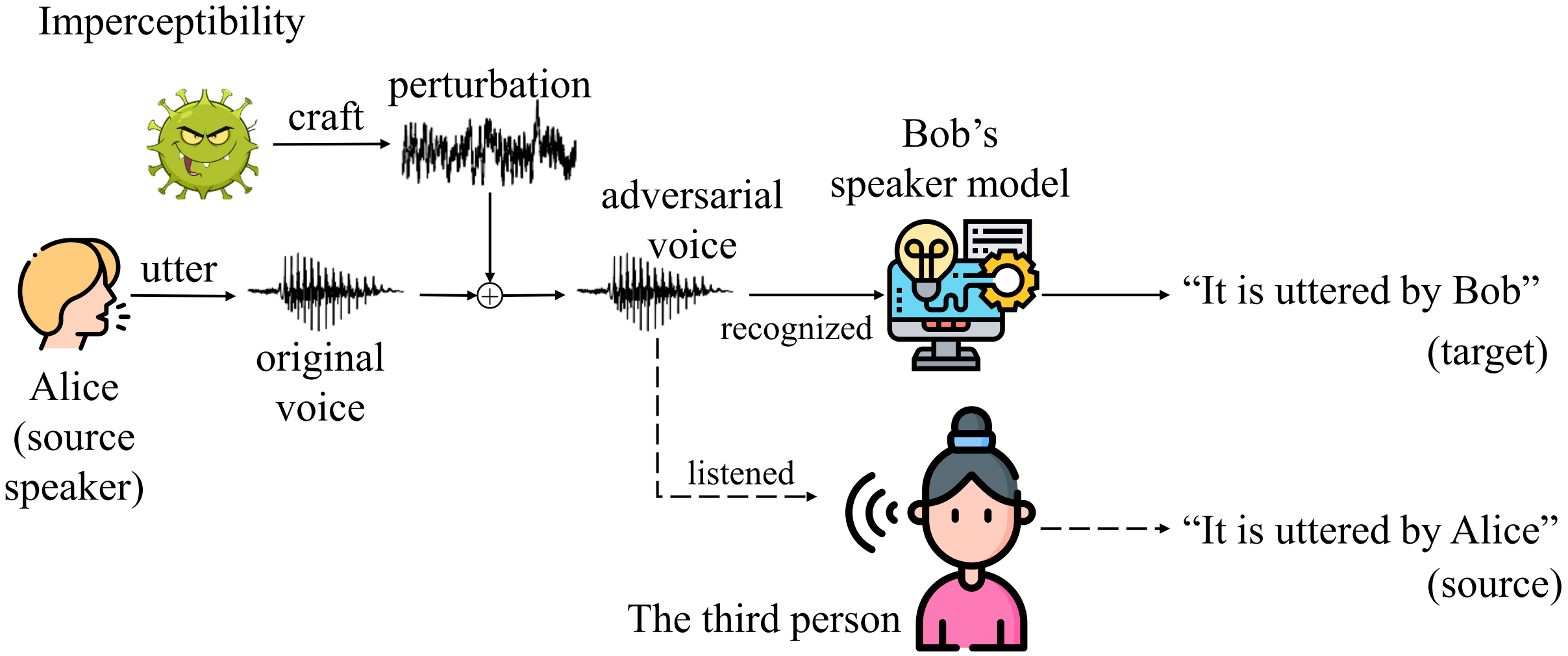
Imperceptibility
craft
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Bob's
speaker model
adversarial
voice
utter
original
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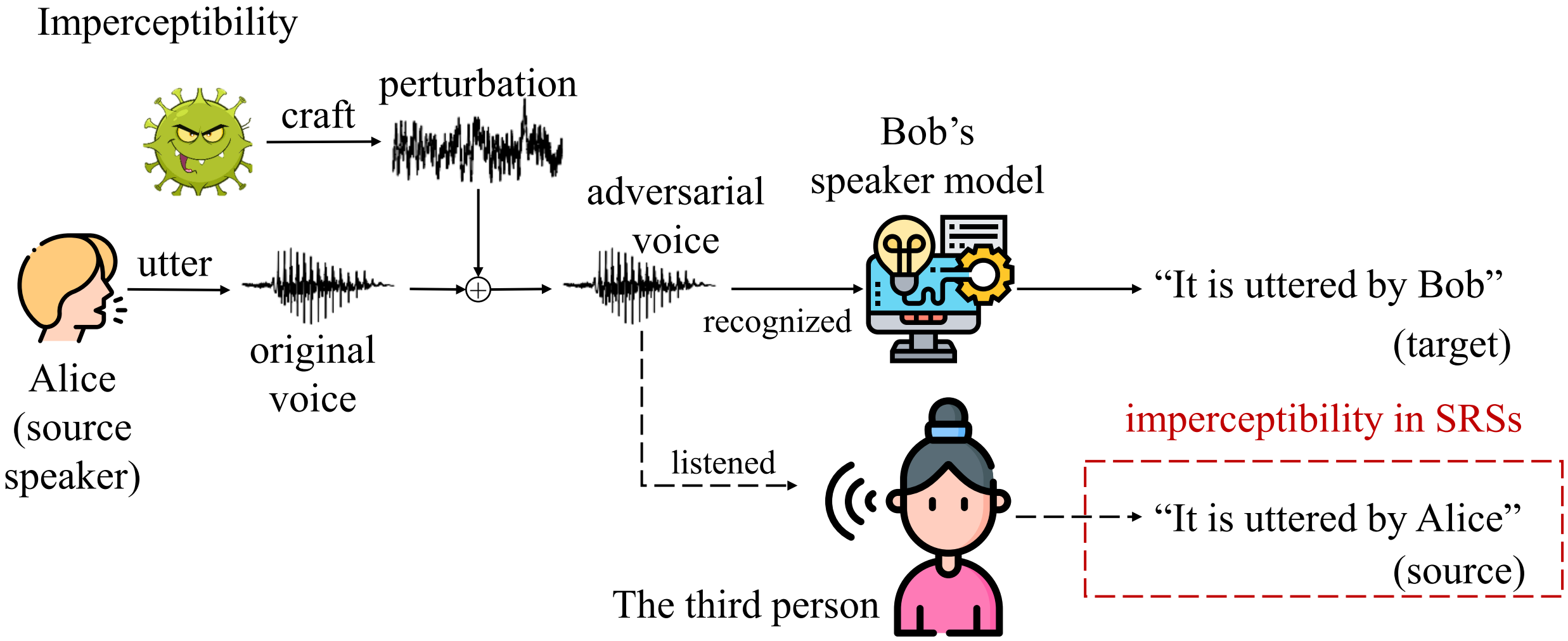
"It is uttered by Bob"
(target)
Alice
(source
speaker)
listened
"It is uttered by Alice"
(source)
The third person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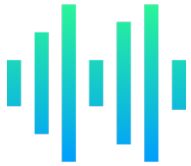
Take away:

1. Black-box and practical adversarial attack against speaker recognition systems
2. Effective to commercial speaker recognition services
3. Effective in over-the-air attack
4. Imperceptible to human hearing

FAKEBOB Website:
https://sites.google.com/view/fakebob/home

FAKEBOB Code:
https://github.com/FAKEBOB-adversarial-attack/FAKEBOB





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