Practical adversarial attack against speech recognition platforms

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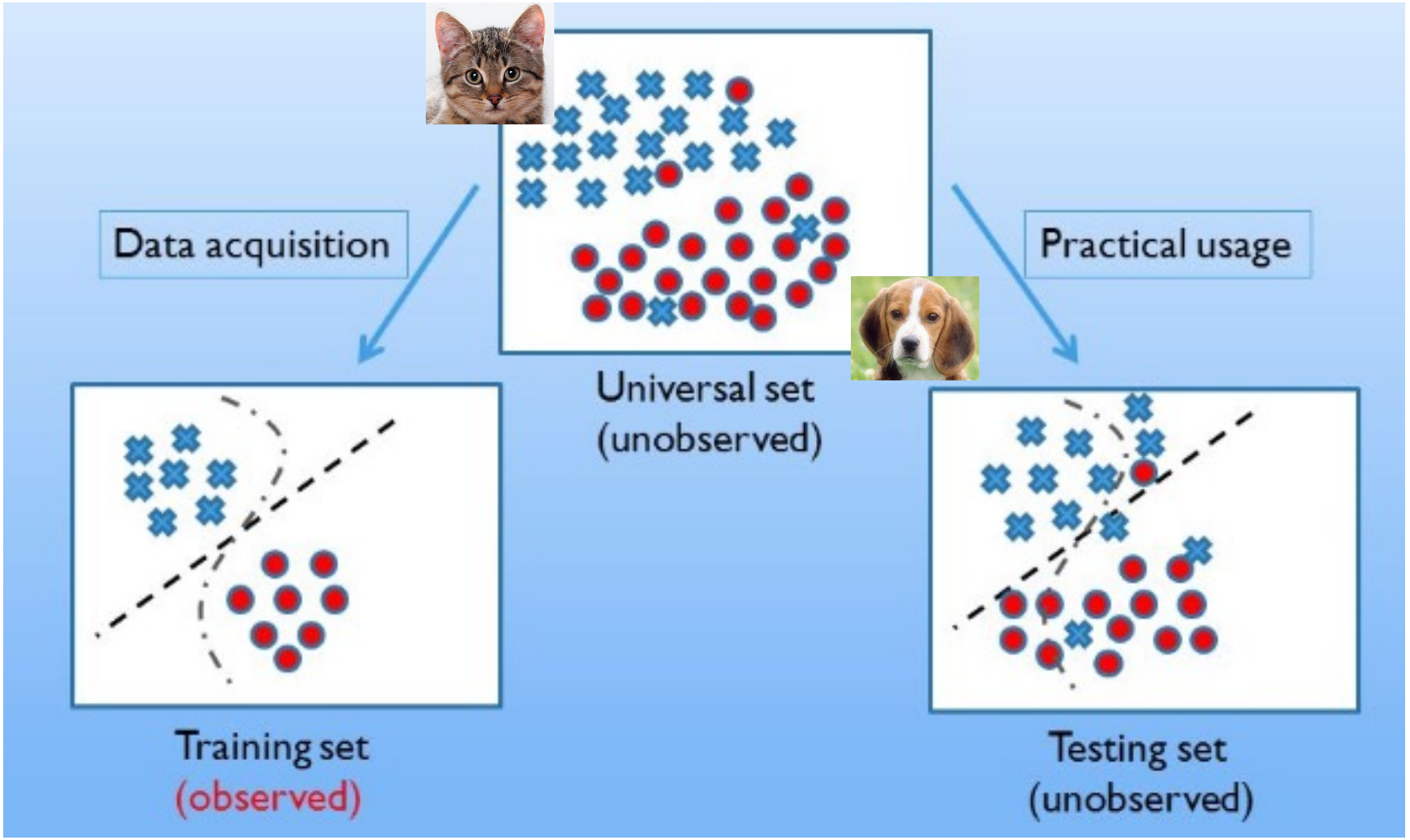
About me

- Shengzhi Zhang
  - Ph.D., Penn State University, 2012
  - Bachelor, Tongji University, 2006
- Assistant professor, CS, Boston University MET College (2018.07 –)
- Experience
  - Assistant professor, CS, Florida Tech (2014.01 – 2018.07)
  - IBM research lab, Honeywell aerospace lab, Cisco R&D
- Cybersecurity research:
  - Machine learning security
  - Vehicle security
  - Operating system security
  - Zeroization verification
  - Cloud computing
  - …

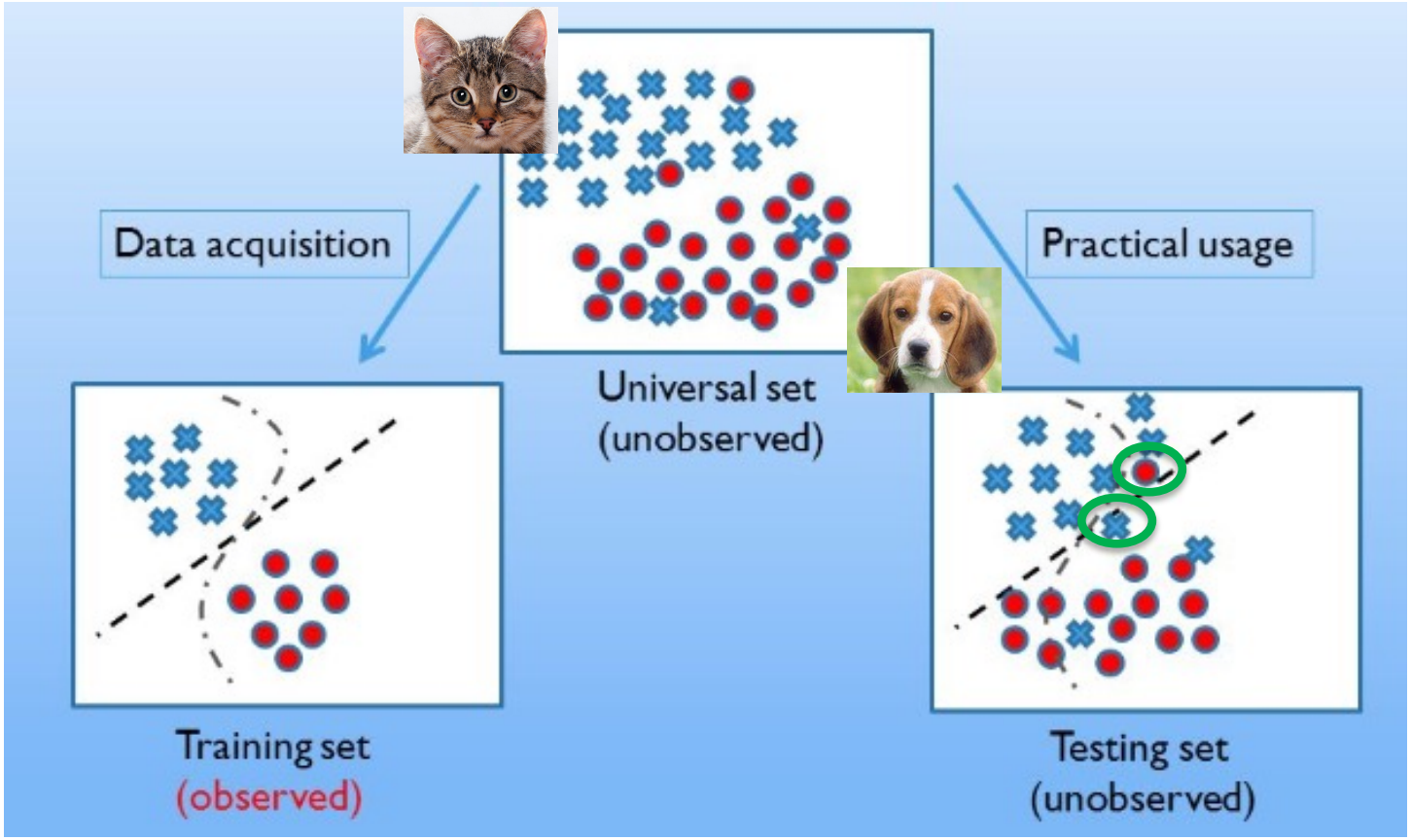
Outline

- **What is adversarial attack?**
- Our research
- Conclusion

What is machine learning?



Adversarial Attack



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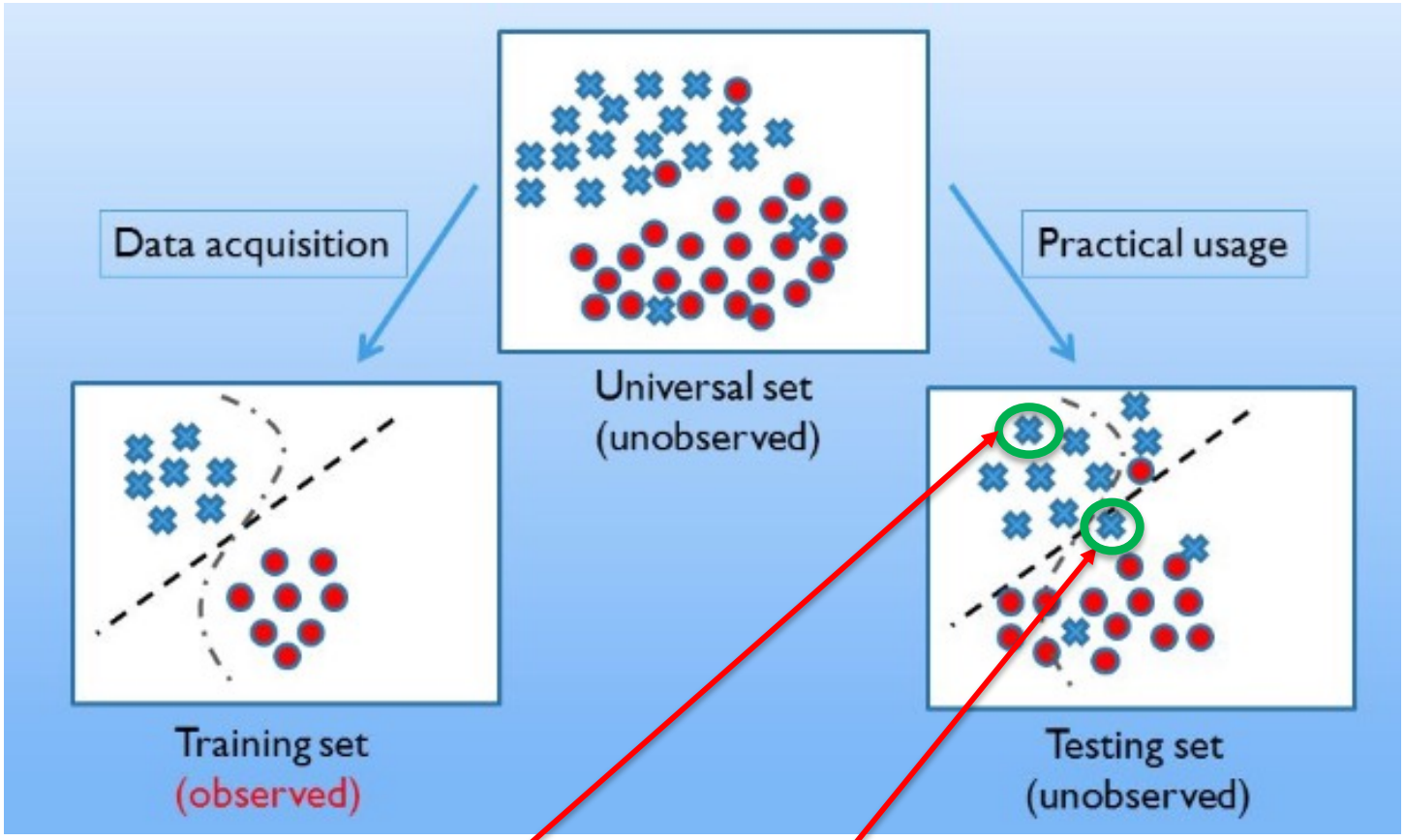

Confusion for self-driving vehicles

Original Inputs

Modified Inputs

Wrong ML Detection

Existing Research

- **Image (lots of works)**
  - White box, black box
  - Digital, physical
- **Video (leverage findings on image)**
  - White box, limited black box and blind
  - Digital, limited physical

- **Audio (few works)**
  - Mostly white box
  - Mostly digital
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Speech Recognition

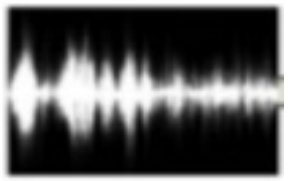
Echo, unlock the front door

Echo, unlock the front door

Adversarial attacks against speech recognition?

Echo, unlock the front door

Soft music with perturbation added



Hmm, quality of the soft music is not so good.

Step 1: White Box Attack

- Methodology:
  - Impact many users in an automated fashion
    - Revise song/music
  - Generate impossible or difficult to be noticed adversarial samples
    - Revise enough
    - Revise little
  - Attack in the physical world (practical attack)
    - Modeling random noise to accommodate background noise, electronic noise from speakers

CommanderSong: A Systematic Approach for Practical Adversarial Voice Recognition , USENIX Security '18

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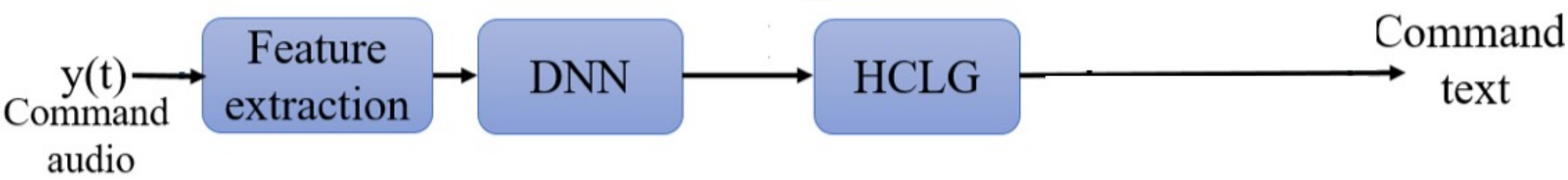
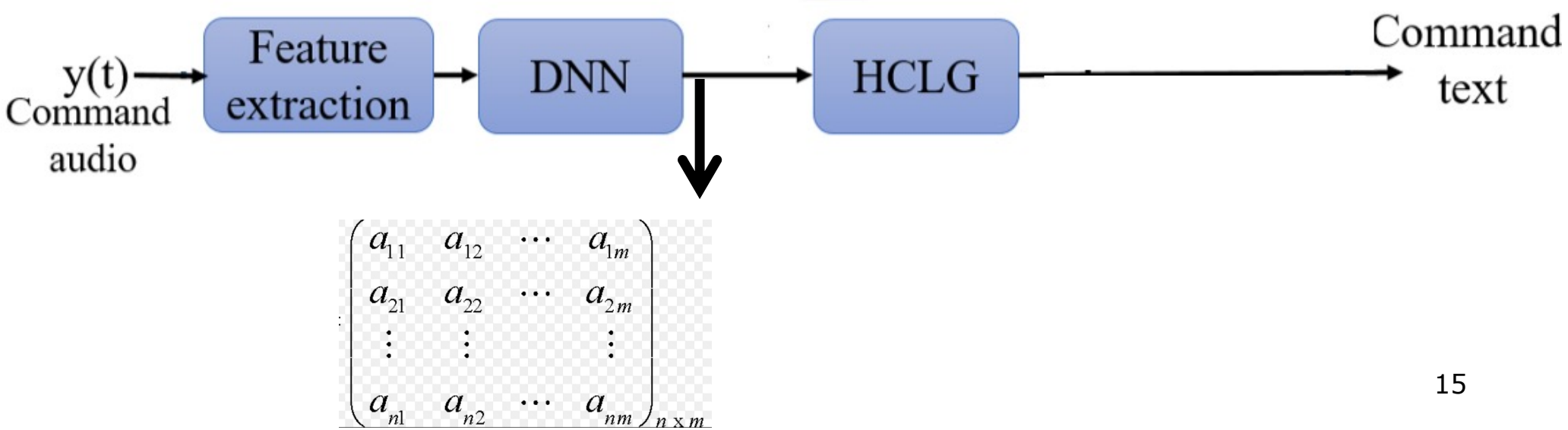
okay google call one one zero one one nine one two zero

Typical Speech Recognition: Kaldi



Our Approach



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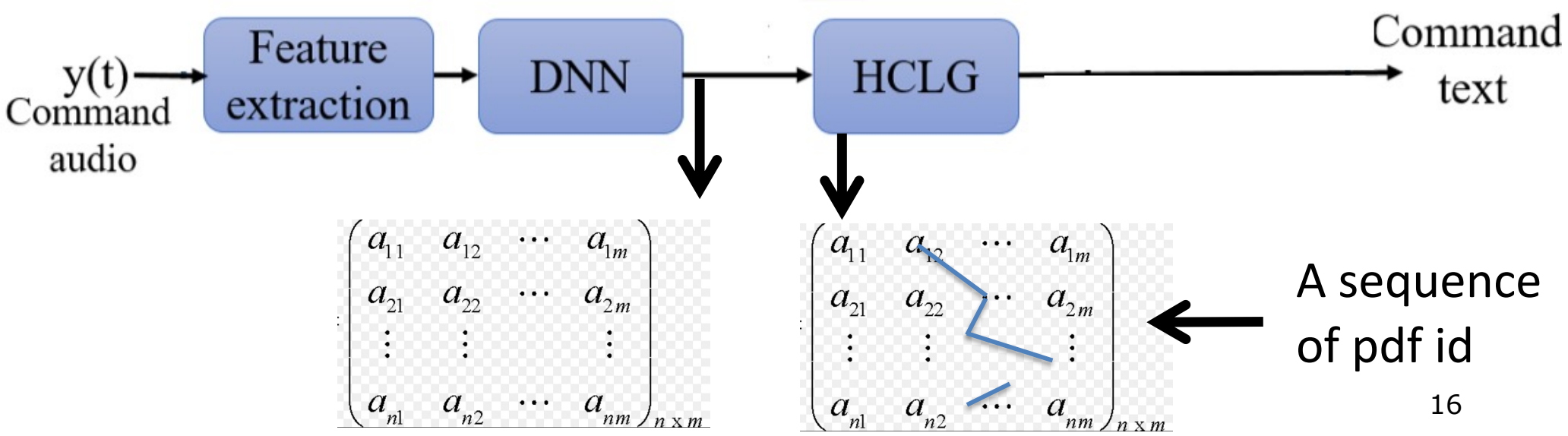

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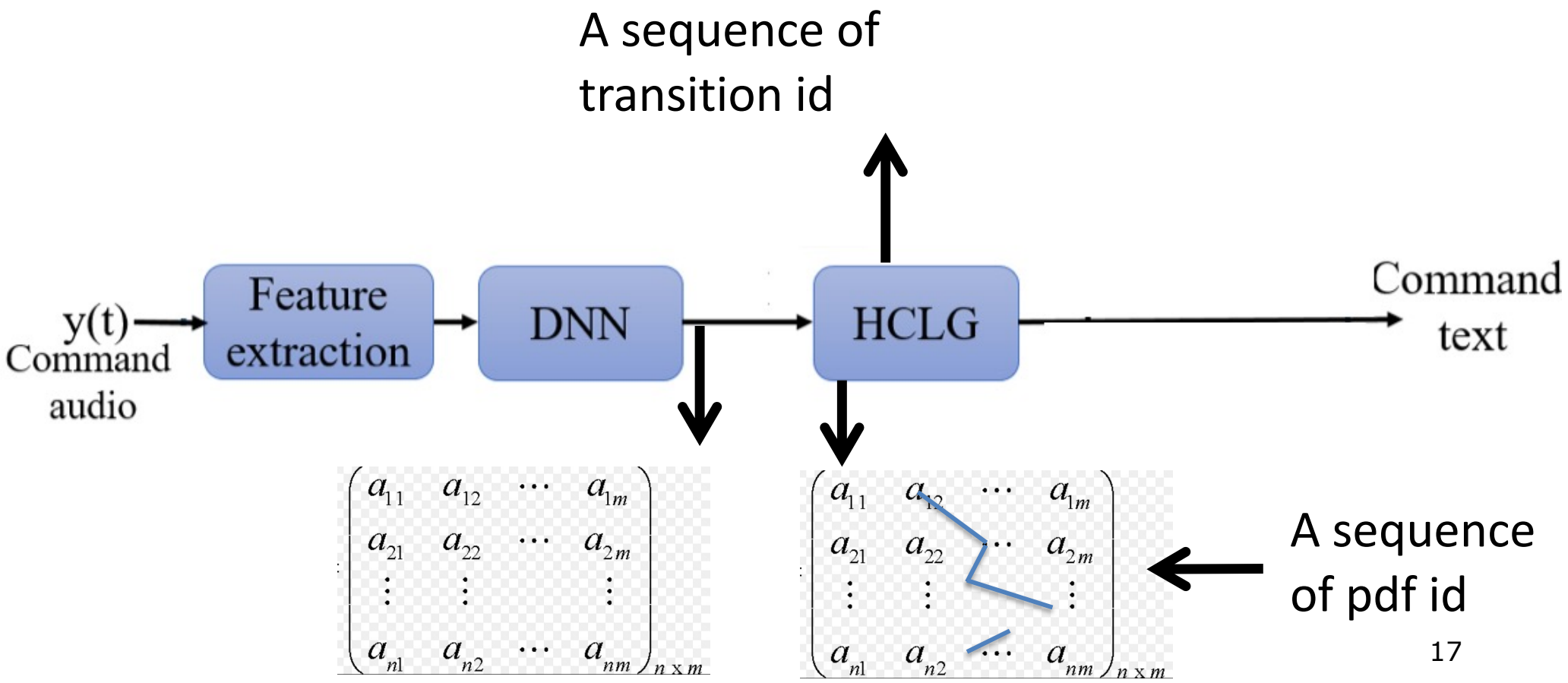

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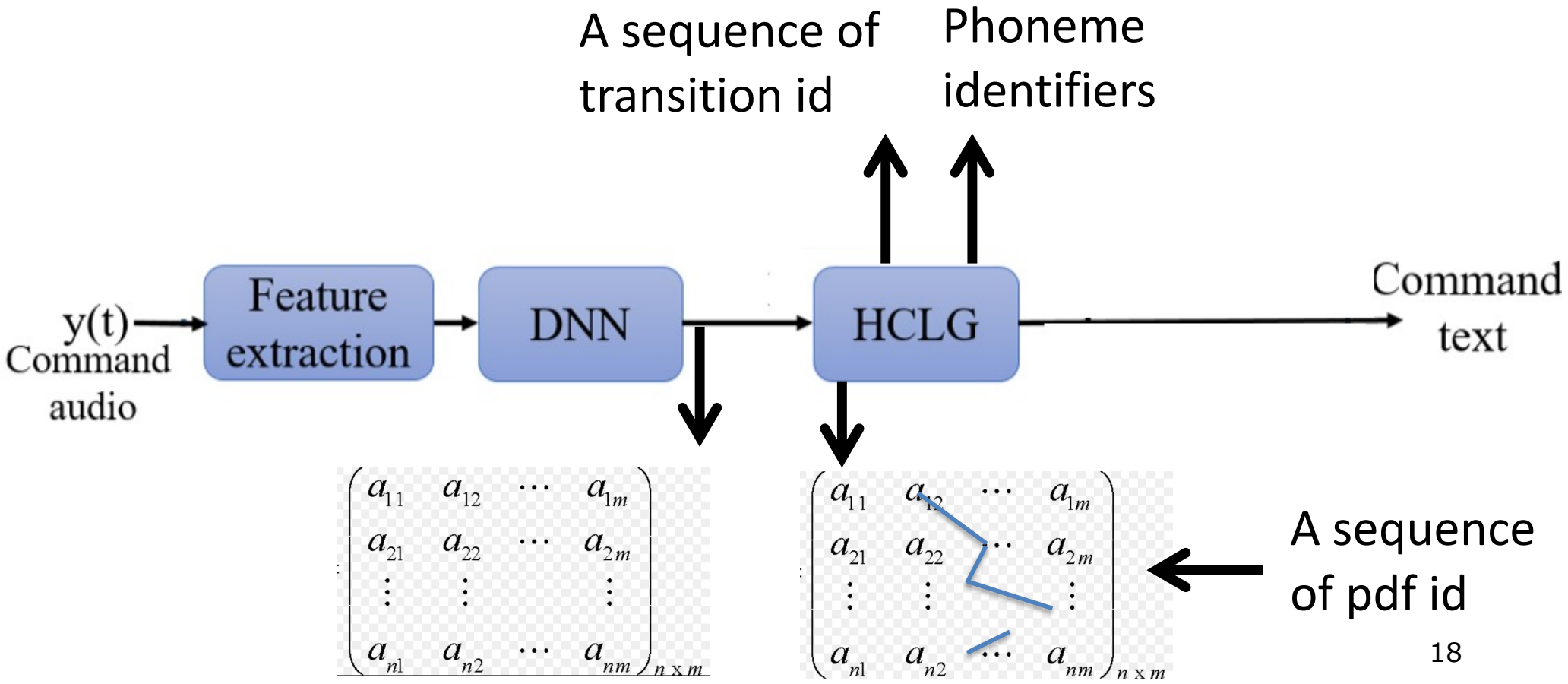

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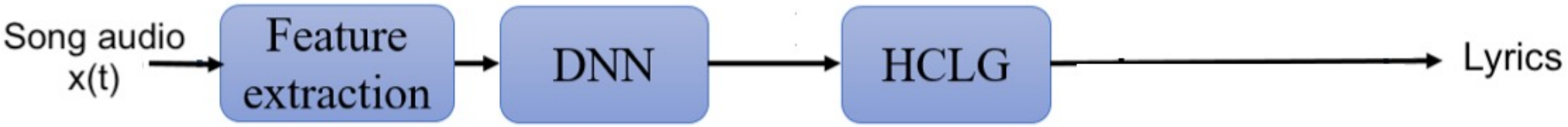
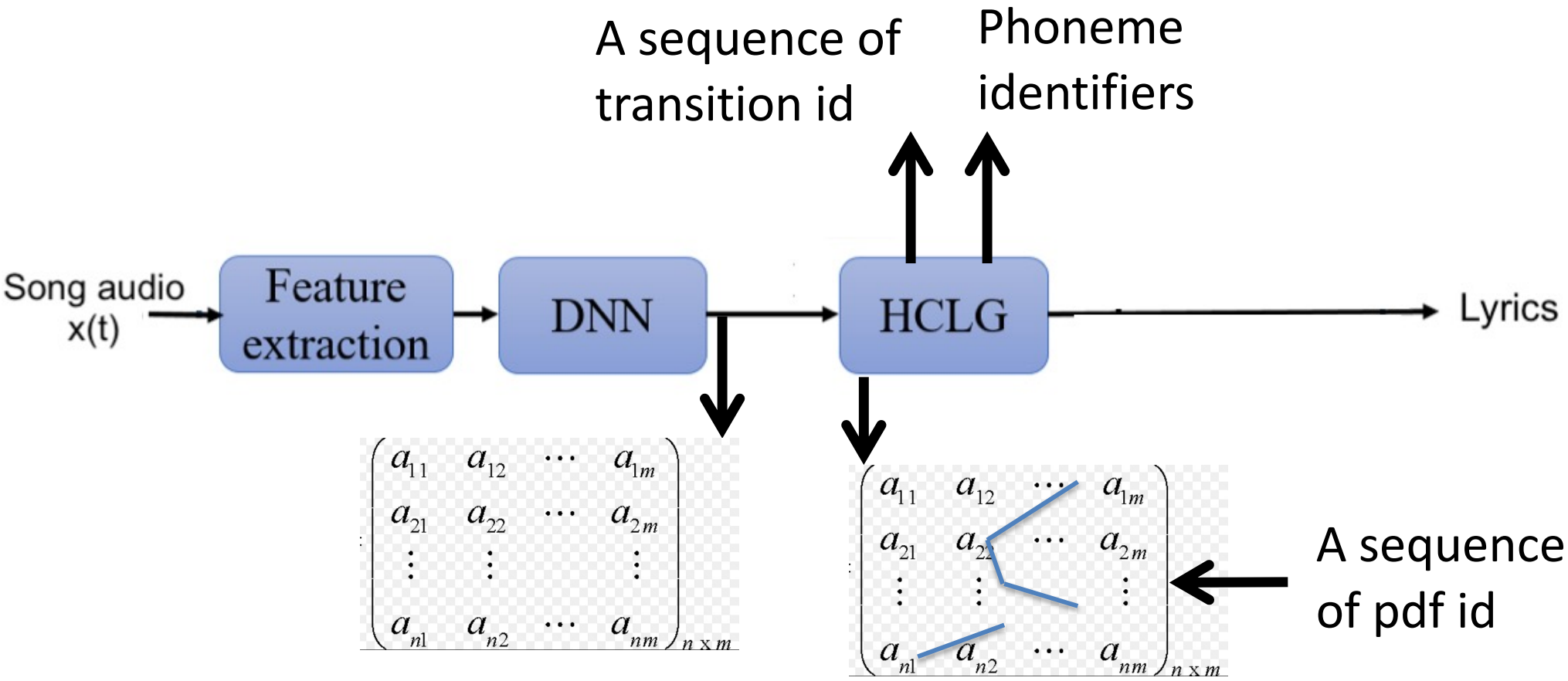
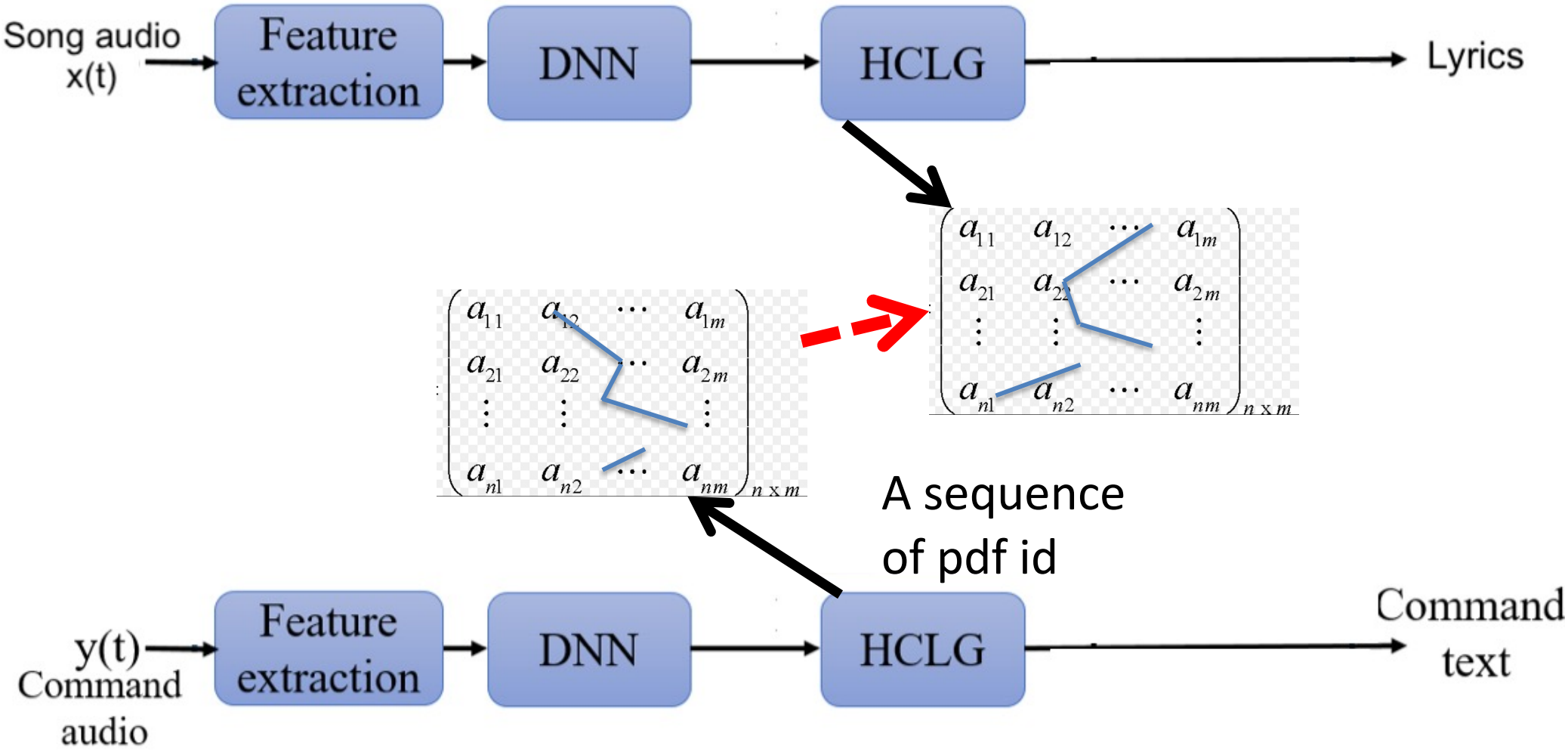



A sequence of transition id
Phoneme identifiers
Song audio x(t)
Feature extraction
DNN
HCLG
Lyrics
A sequence of pdf id

Our Approach



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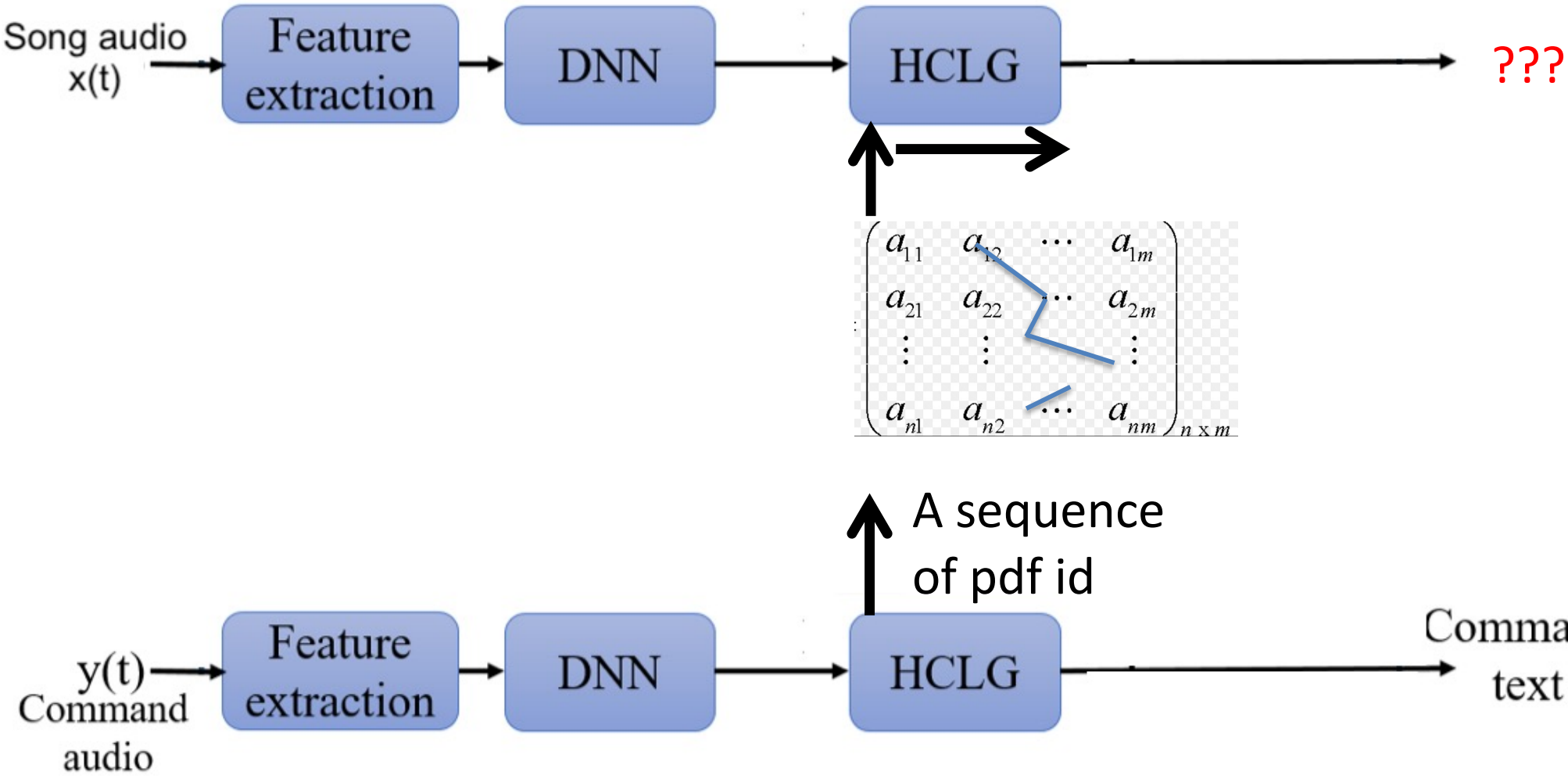

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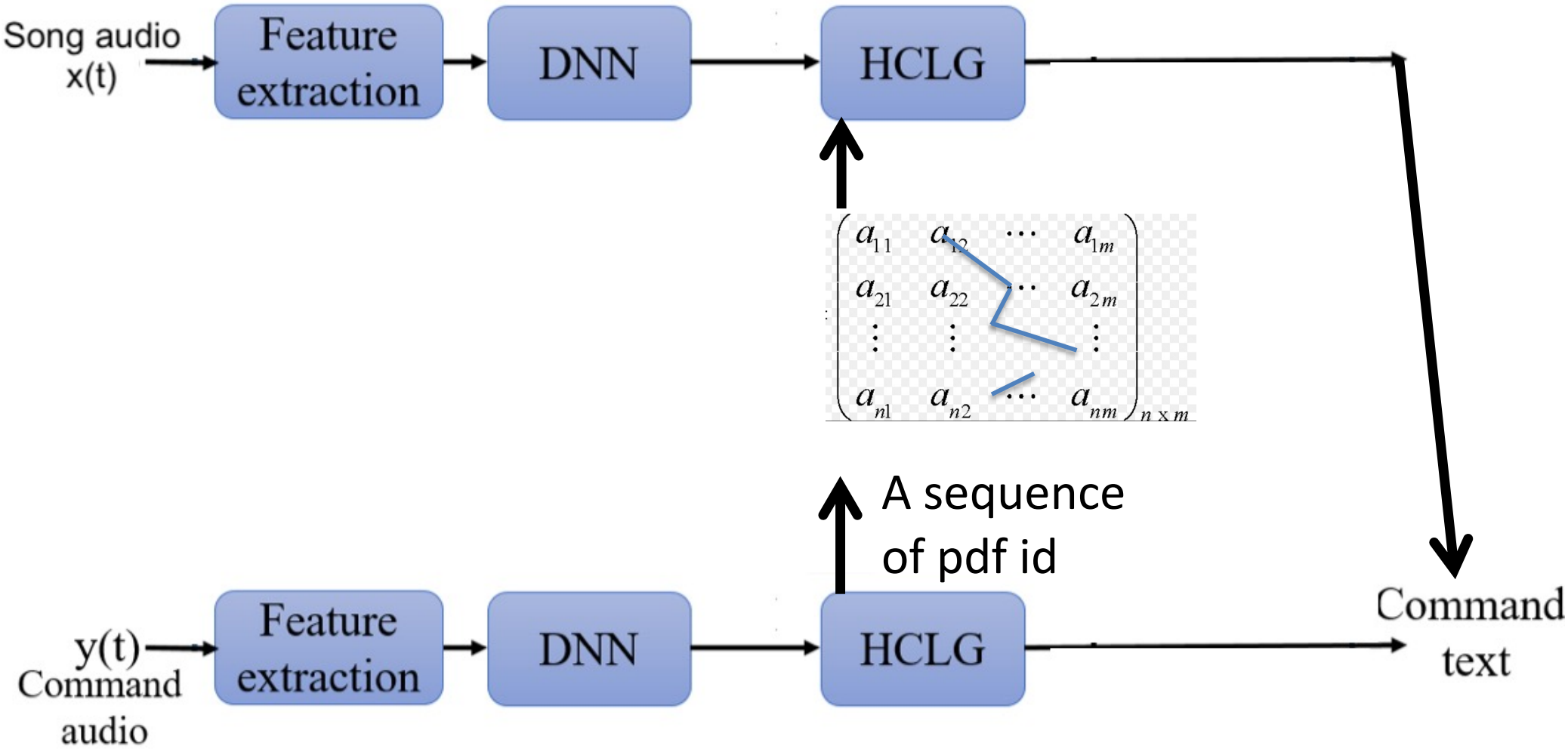

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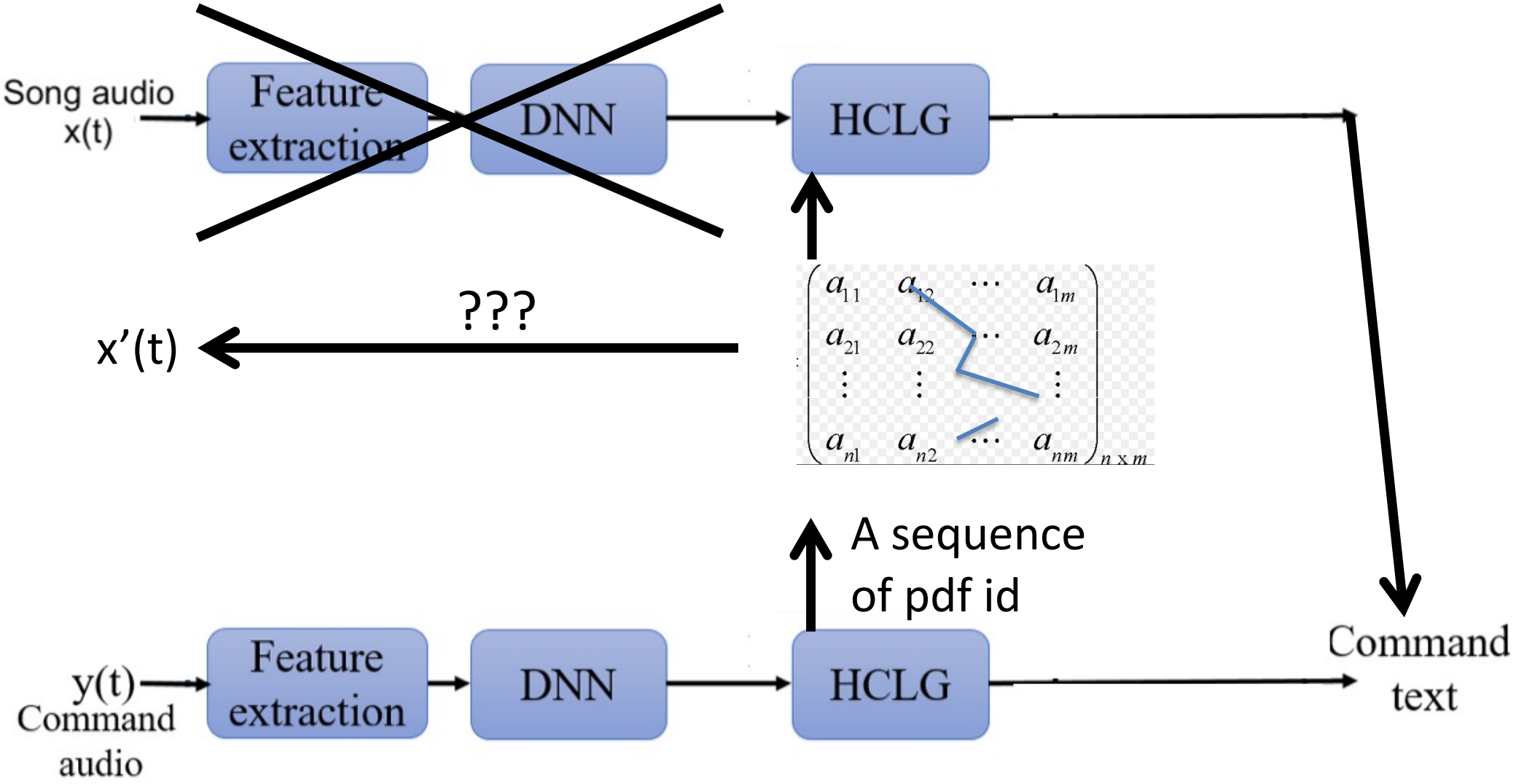

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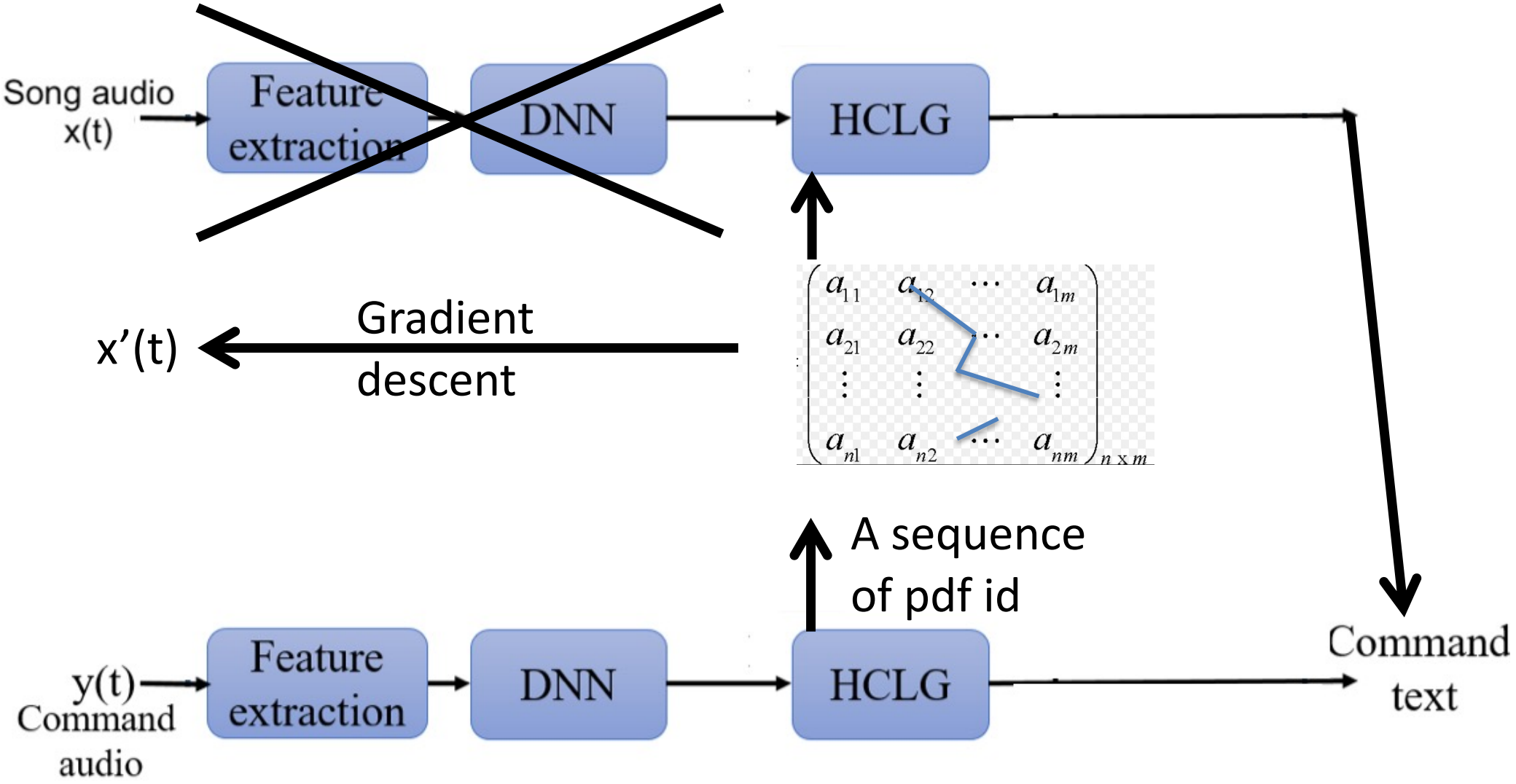
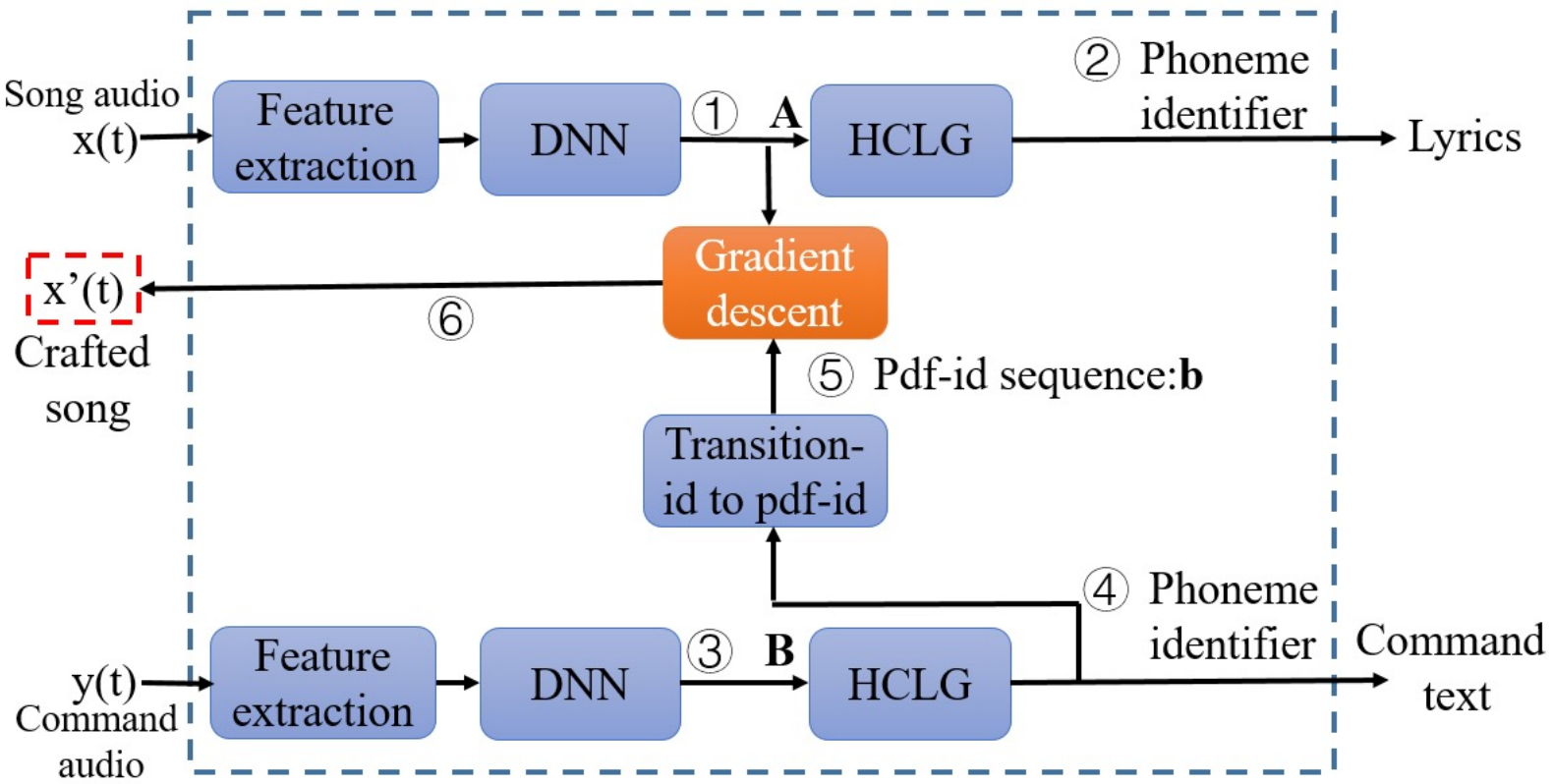


Dealing with Noise



$$\arg\min_{\mu(t)} \quad \|g\left(x(t)+\mu(t)+n(t)\right)-\mathbf{b}\|_1, \qquad (2)$$

Step 2: Black-Box Attack

- Attack what?
  - Google Home, Amazon Echo
  - Google Assistant, Microsoft Cortana, Apple Siri running on smartphone
- Challenges (even you know how to attack physically)
  - You know nothing about the model
  - It fails to respond even if you directly talk to it!

Devil's Whisper: A General Approach for Physical Adversarial Attacks against Commercial Black-box Speech Recognition Devices, USENIX Security 20

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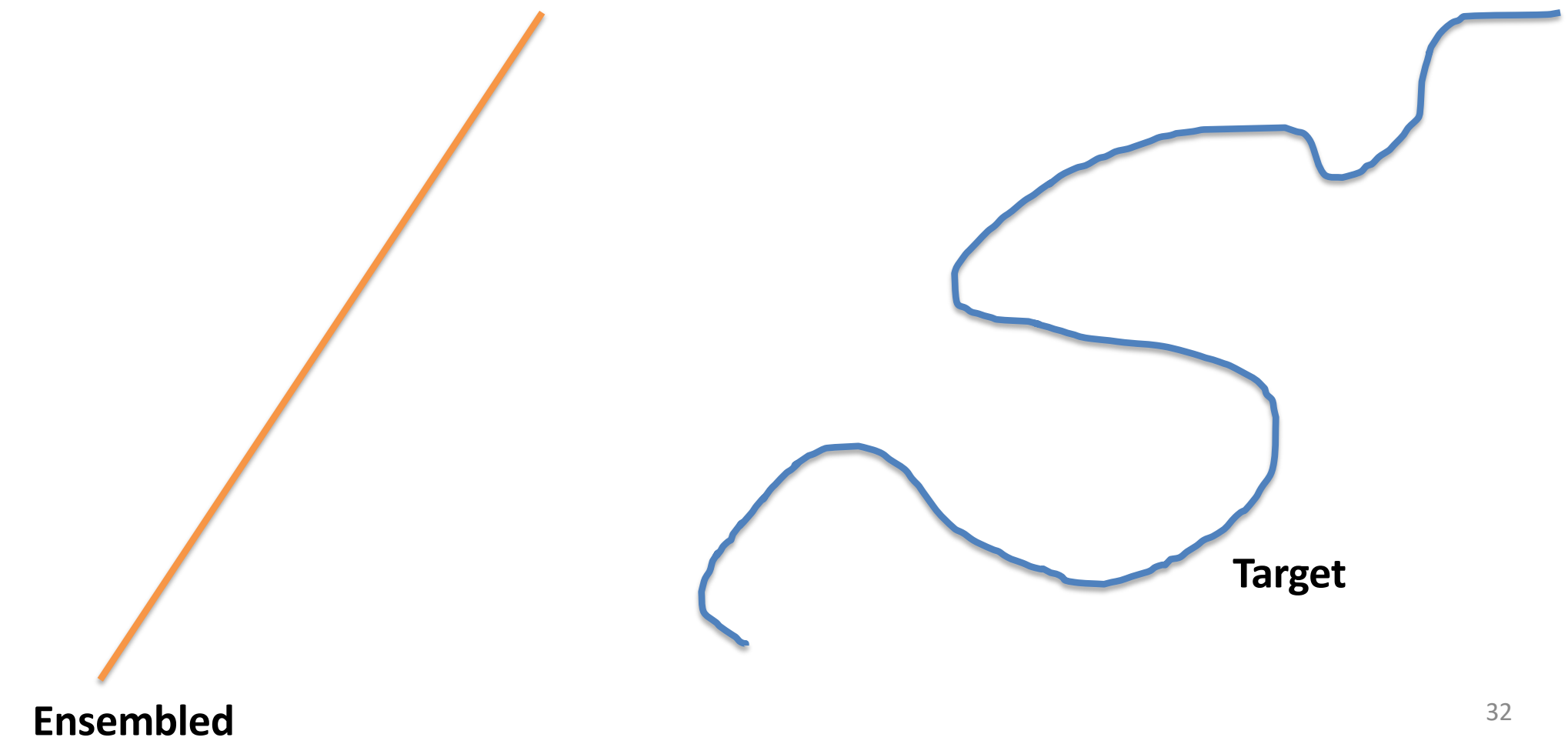
  - Finally
    - Ensemble a local substitute model and a complete model
    - Both are white box

Step 2: Black-Box Attack

- Interpretability
  - Decision boundary in high dimensional space



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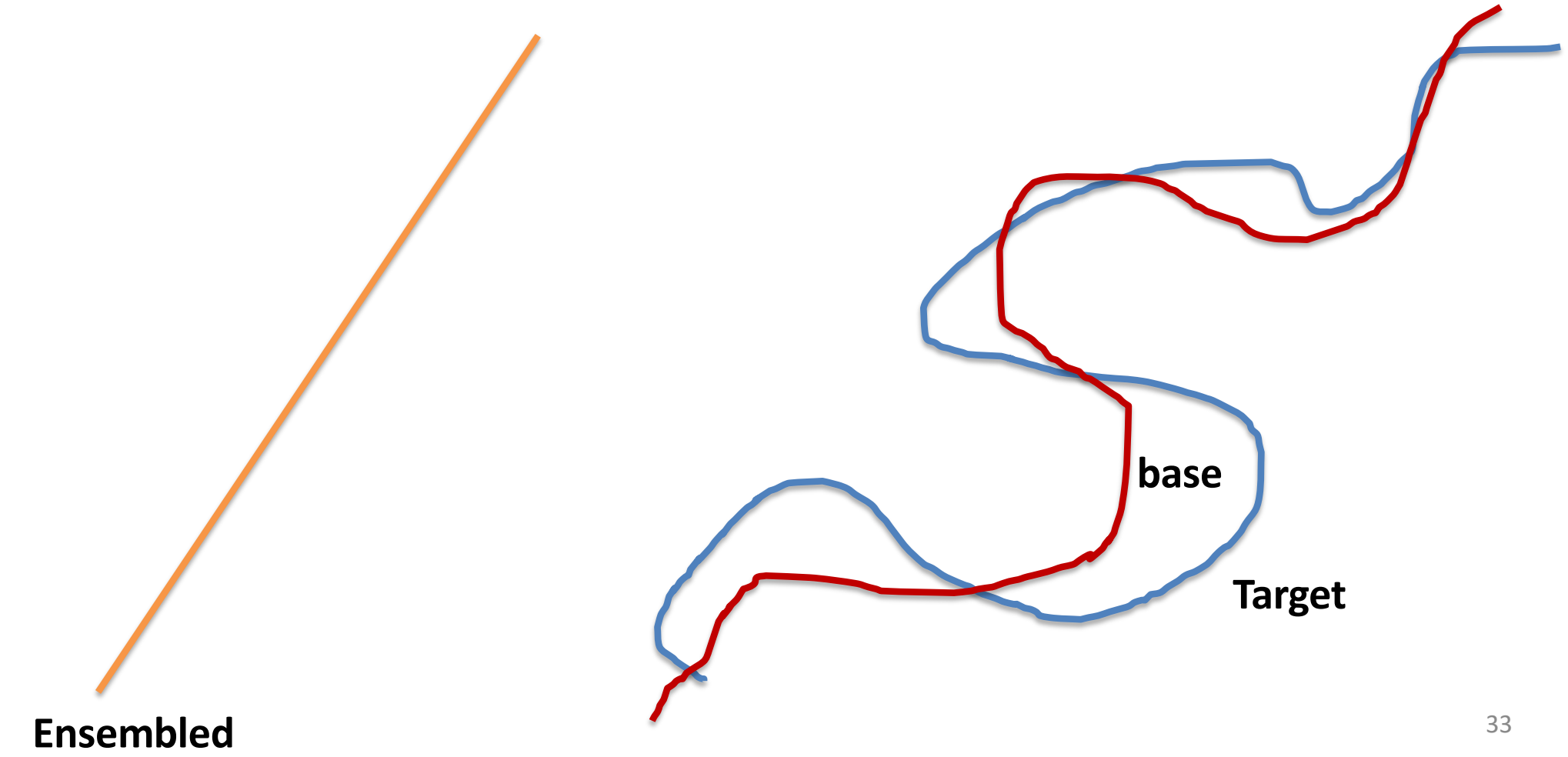

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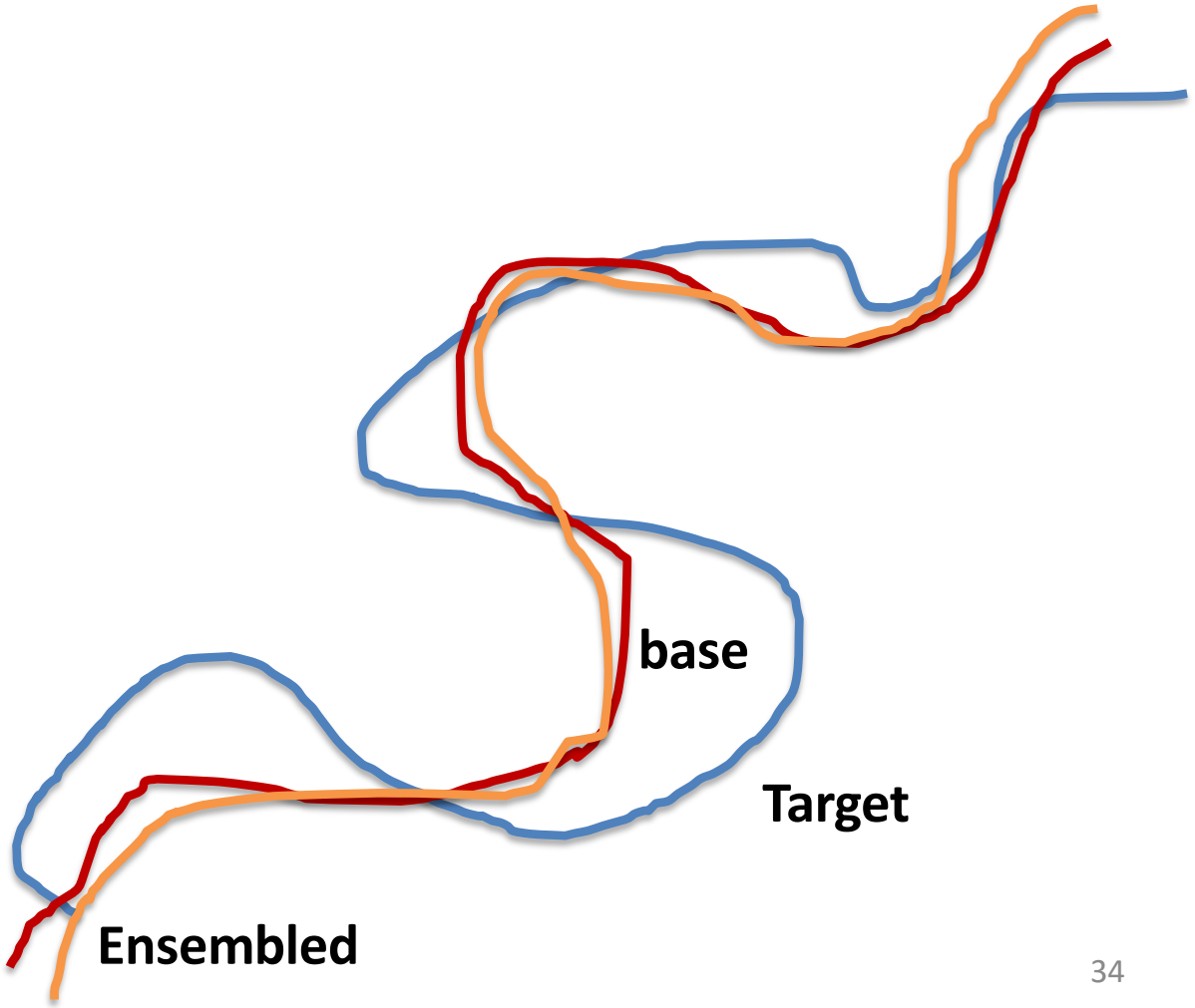

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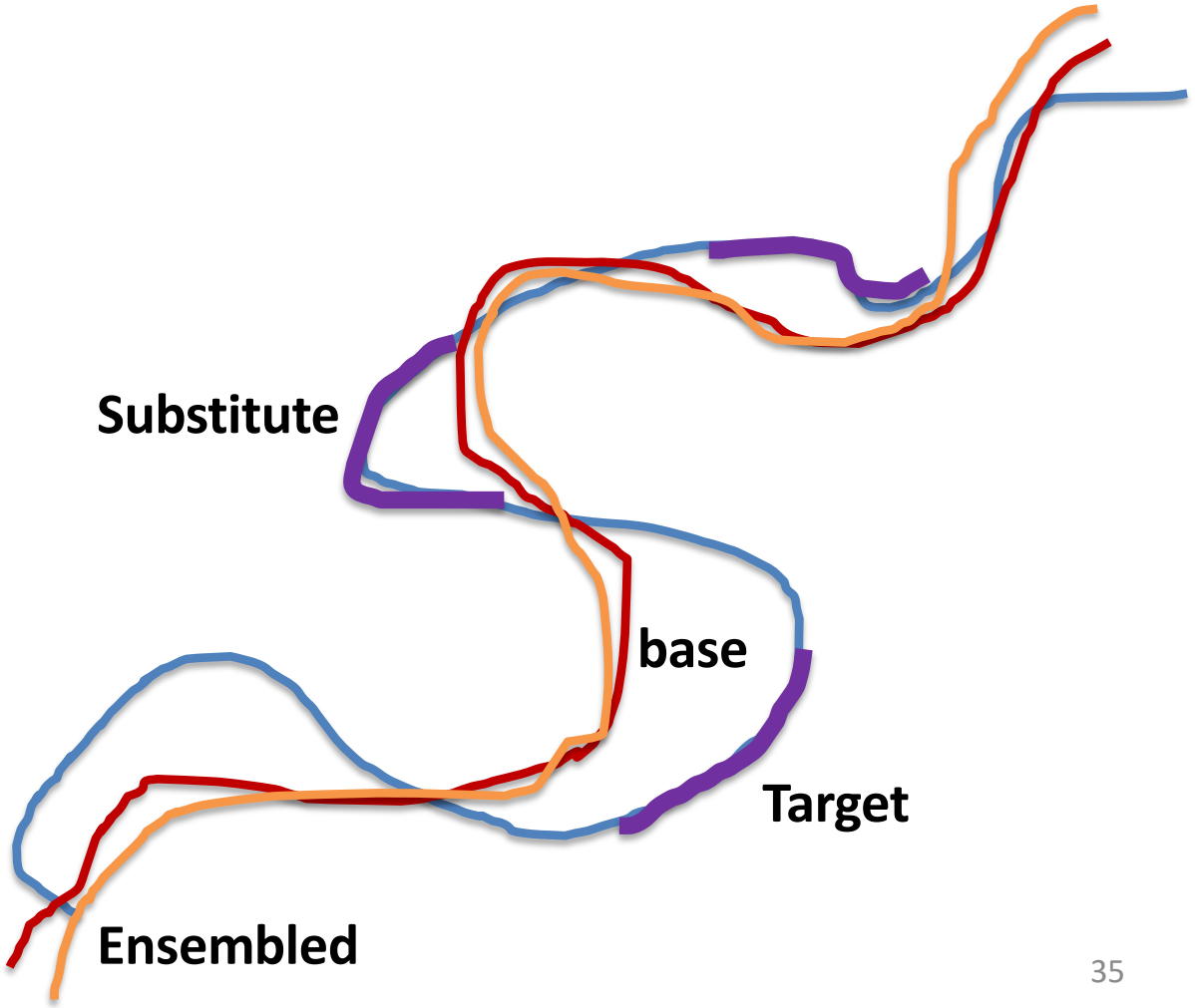

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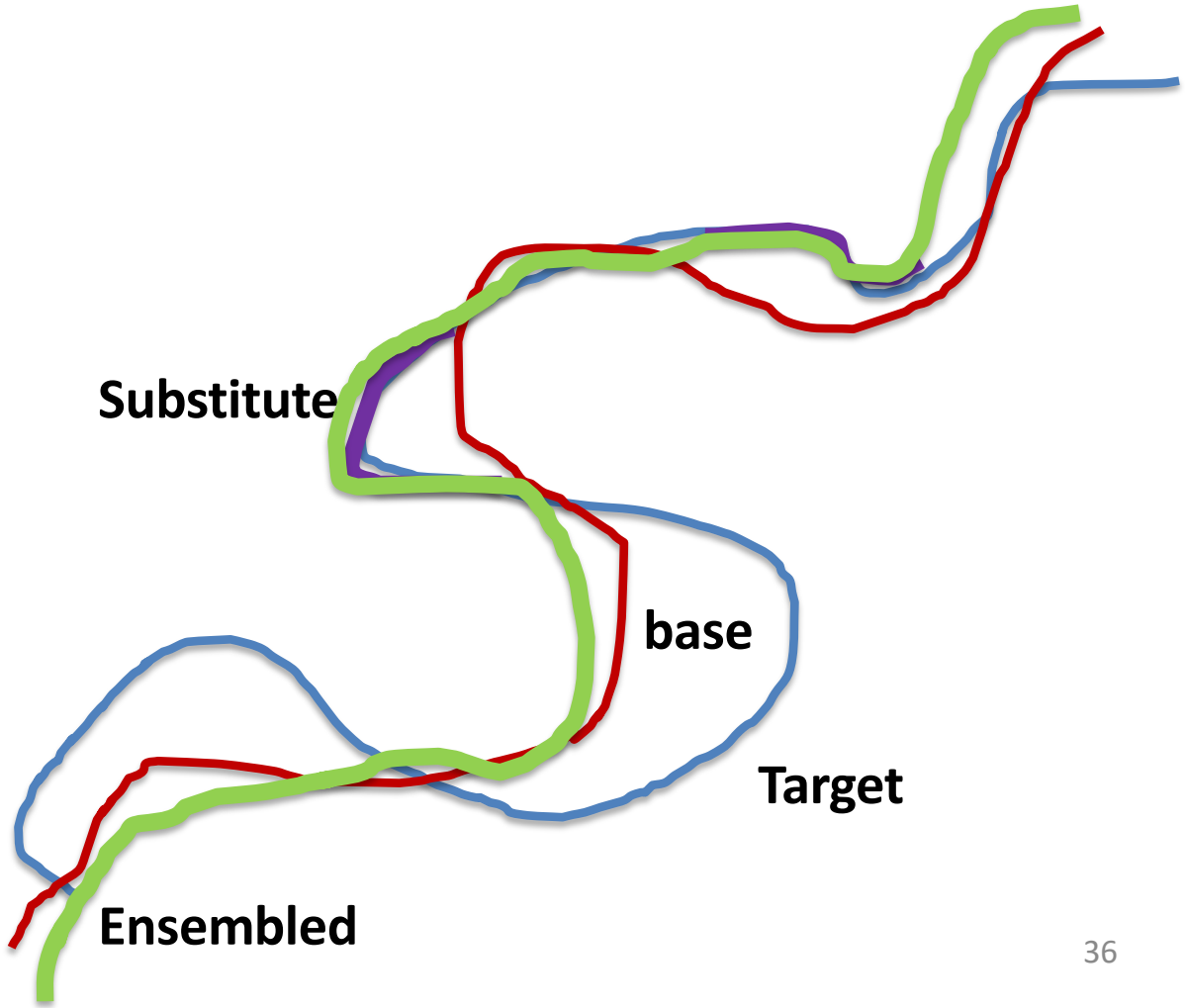

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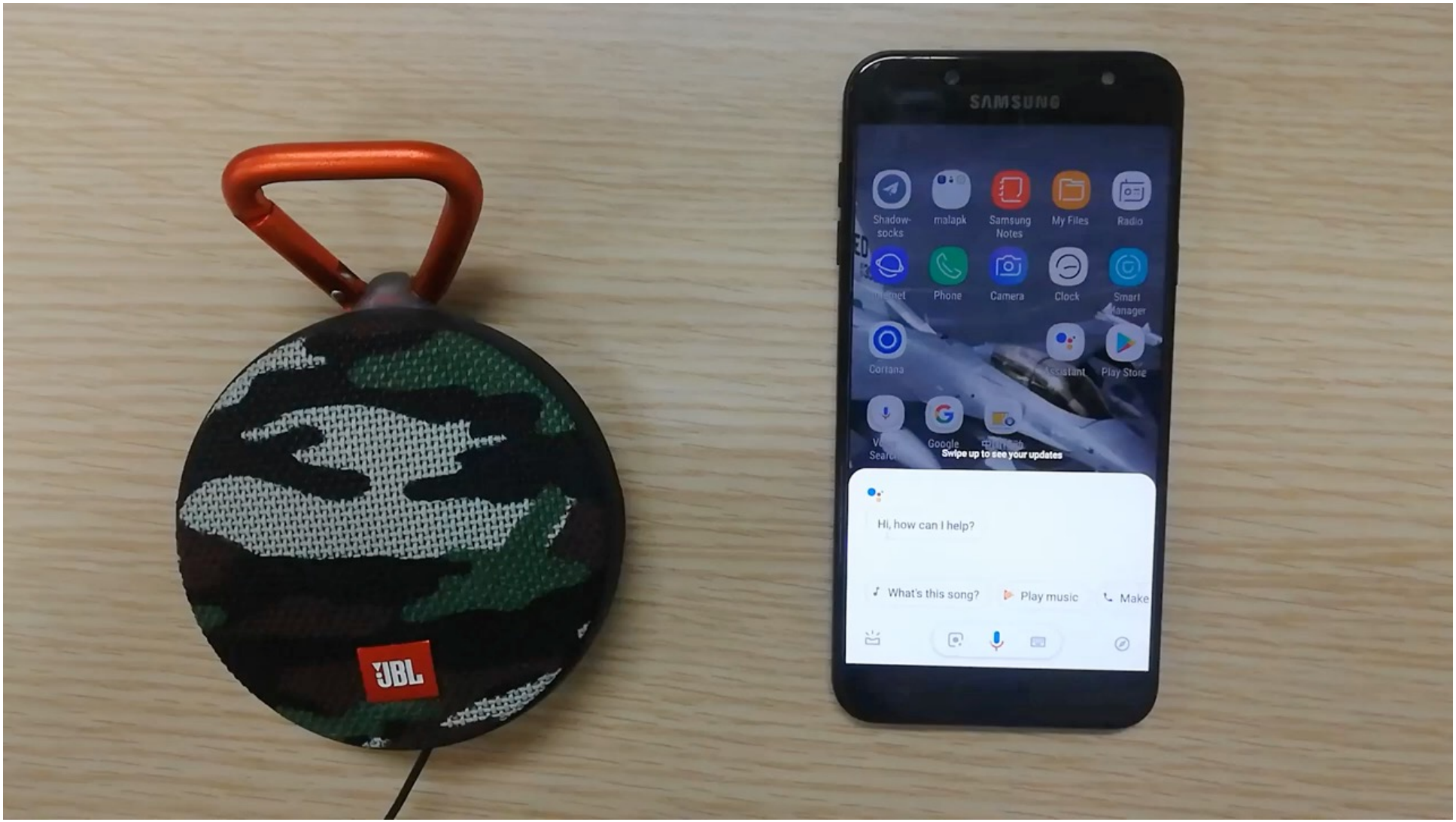

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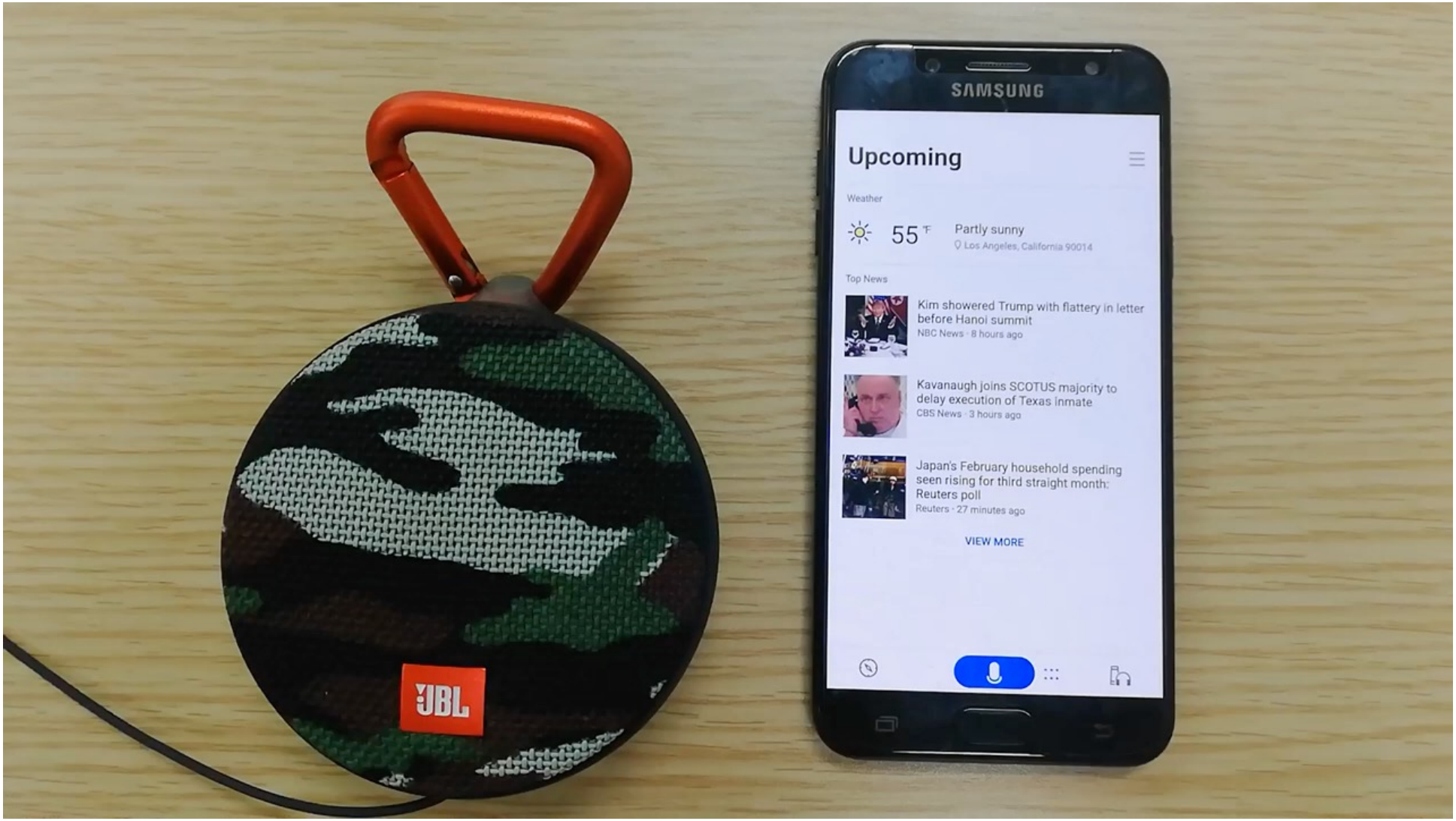

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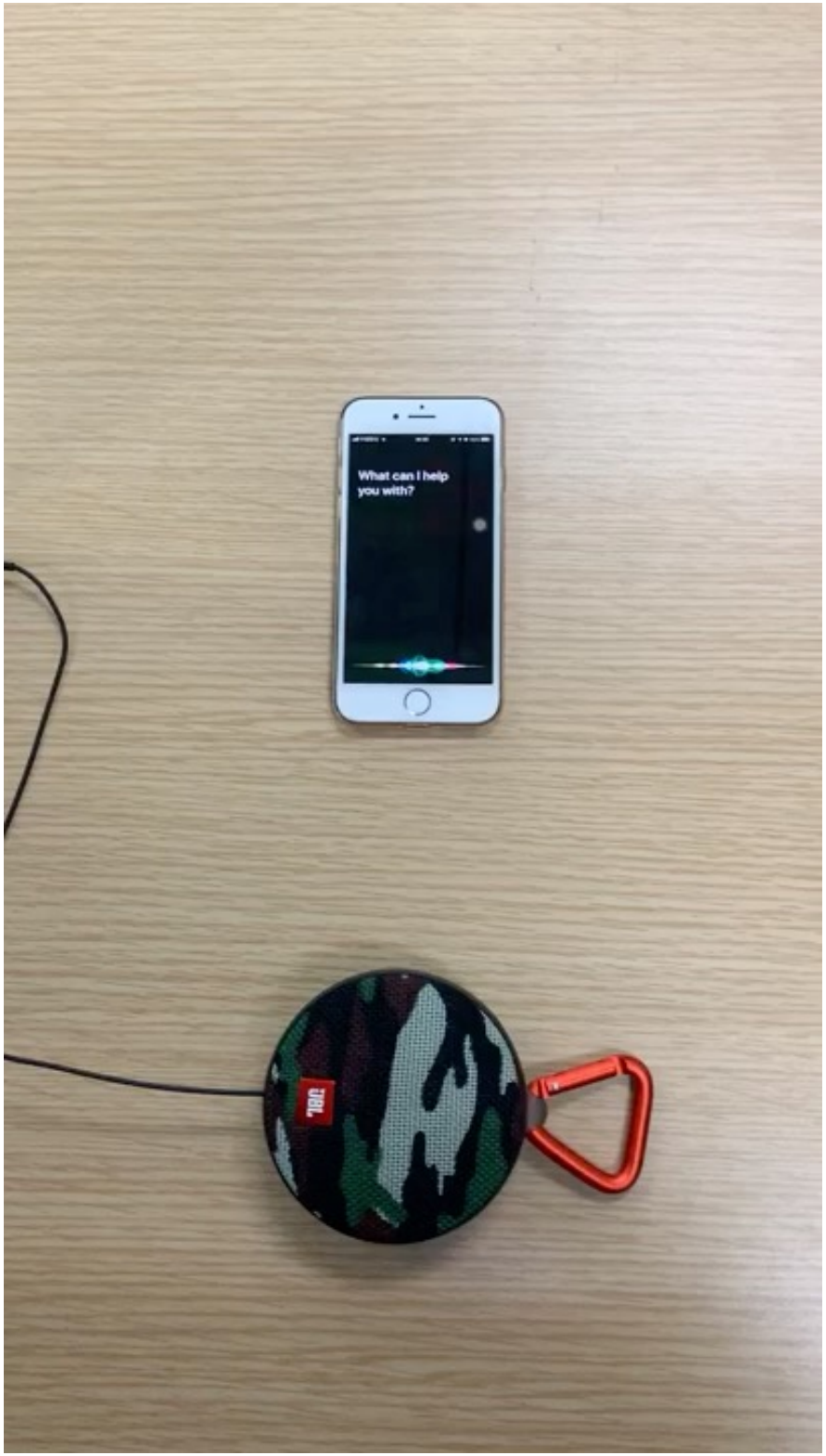

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- **Conclusion**

Conclusion

- Attacks are feasible
  - Image, audio, video
  - Digital, physical
  - White box, black box
- **Defense**
  - Quite limited and specific
    - Examine the distribution of training dataset
    - Smoothen the gradient
  - General approach to defend machine learning is demanded


Thank You!