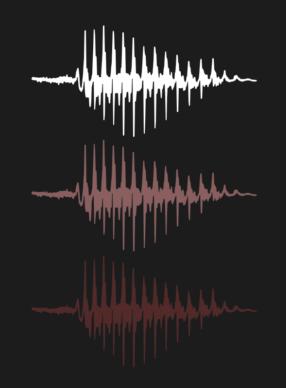
Adversarial Attacks

on Audio Speech Recognition systems



LINKMEDIA TEAM

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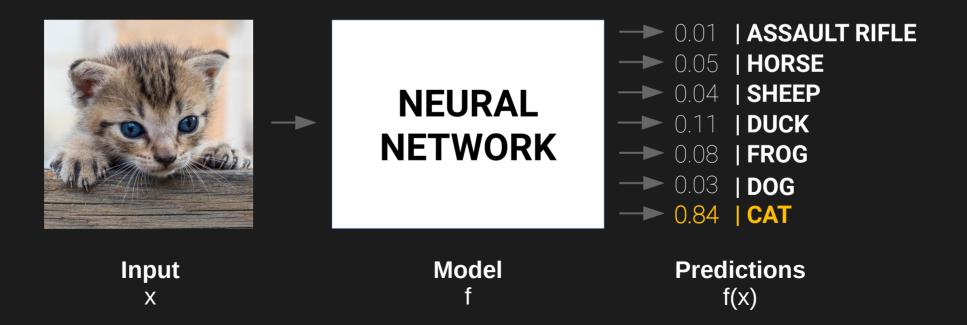
Deep Learning & applications

Machine Learning
ML

Learning **automatically** from a set of data to perform a task without explicit programmation.

Deep Learning
DL

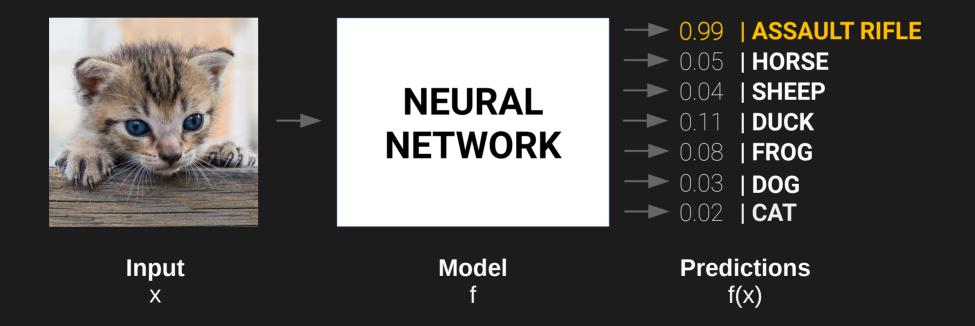
Methods of ML that use **neural networks**.



Deep Learning & security

Adversarial Example

A seemingly benign input that fools a neural network.



Neural Networks

Powerful graphs

Weighted / Directed

• Forward propagation

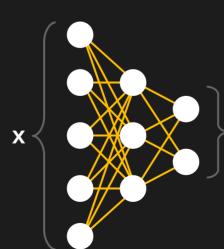
How information is processed.

• **Back** propagation

How a neural network is trained.

Layers of **neurons** with **weighted connections**. Acts as an **ajustable** function $f(\theta, \mathbf{x})$

out = $\Phi(I_1 * W_1 + I_1 * W_2 + I_1 * W_3 + Bias)$ W₃



predictions f(;, **x**) truth **y** Loss(θ, x, y) θ' = θ -▽_θ Loss

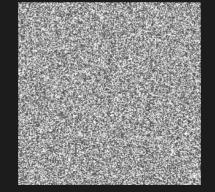
Fast Gradient Sign Method





X

- 0.01 *



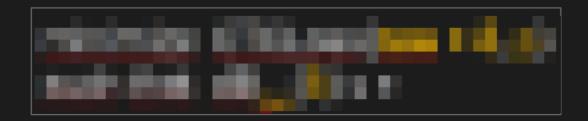
 $\delta = \bigtriangledown$ Loss



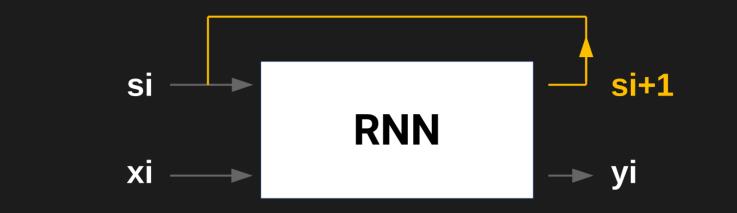
X'

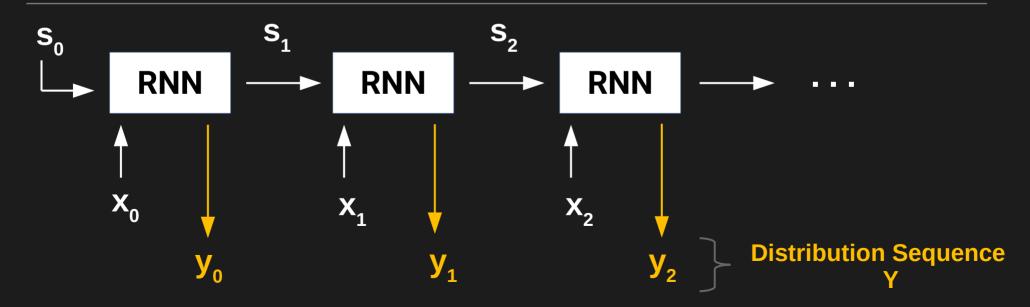
Carlini & Wagner's adversarial attack (1)

- **Targeted** The resulting adversarial example has a **desired** classification.
- White Box Requires full knowledge of the model.
- Minimally Perceptible
 Trying to minimize the perceptibility of the adversarial noise δ.



Recurrent Neural Networks





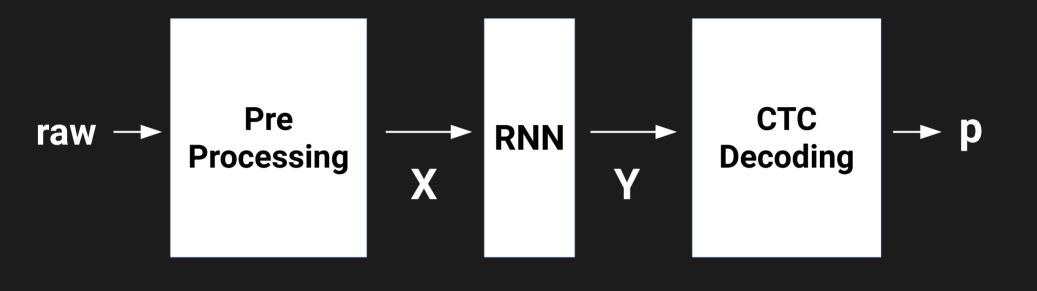
Connectionist Temporal Classification



ε Α Β C	(0.1) 0.2	(0.5 0.1	(0.1) 0.7	(0.1 0.8	(0.0) 0.1	$Pr(\pi \mathbf{Y}) = \prod_{i} \mathbf{Y}_{\pi^{i}}^{i}$
В	0.6	0.2	0.1	0.0	0.0	
С	(0.1)	(0.3)	(0.1)	(0.1)	(0.9)	$Pr(\mathbf{p} \mathbf{Y}) = \sum Pr(\pi \mathbf{Y})$
						$\pi \in \Pi(\mathbf{p}, \mathbf{Y})$

Distribution Sequence Y

DeepSpeech



CTCLoss(raw, p) = - log $Pr(\mathbf{p}|\mathbf{Y})$

Carlini & Wagner's adversarial attack (2)

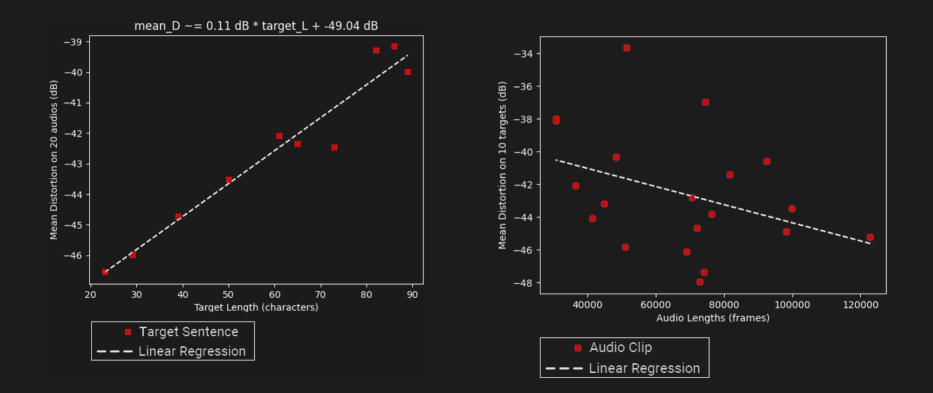
- **Targeted** The resulting adversarial example has a **desired** classification.
- White Box Requires full knowledge of the model.
- Minimally Perceptible
 Trying to minimize the perceptibility of the adversarial noise δ.

$$- \frac{1}{2} = - -$$

minimize $CTCLoss(raw + \delta, p)$ such that $dB_{raw}(\delta) \le \tau$

PyTorch Implementation

• **Methodology** | Targeting 10 different sentences on 20 audios.

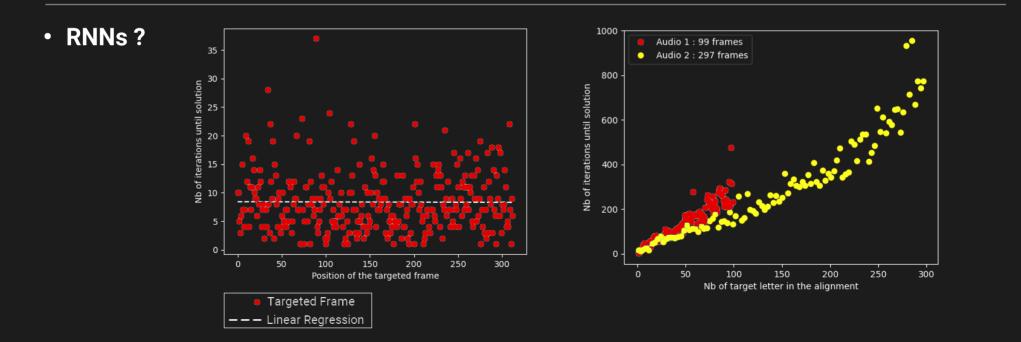


Specificities of audio adversarial attacks

- Distortion Metrics
- $L_{\infty} \& L_{2}$ norms work well for images, not for audio !

• Degrees of non linearity

Differenciating through the **pre-processing** and **CTC decoding** step is not easy.



Conclusion

- Adversarial Attacks are a security and scientific challenge
- Neural Networks are not well understood

• Adversarial Attacks are harder on sequence input

Main References

Intriguing properties of neural networks (2013)

C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow and R. Fergus.

Explaining and harnessing adversarial examples (2014)

I. J. Goodfellow, J. Shlens, and C. Szegedy

Audio adversarial examples: Targeted attacks on speech-to-text (2018) Carlini, N. and Wagner