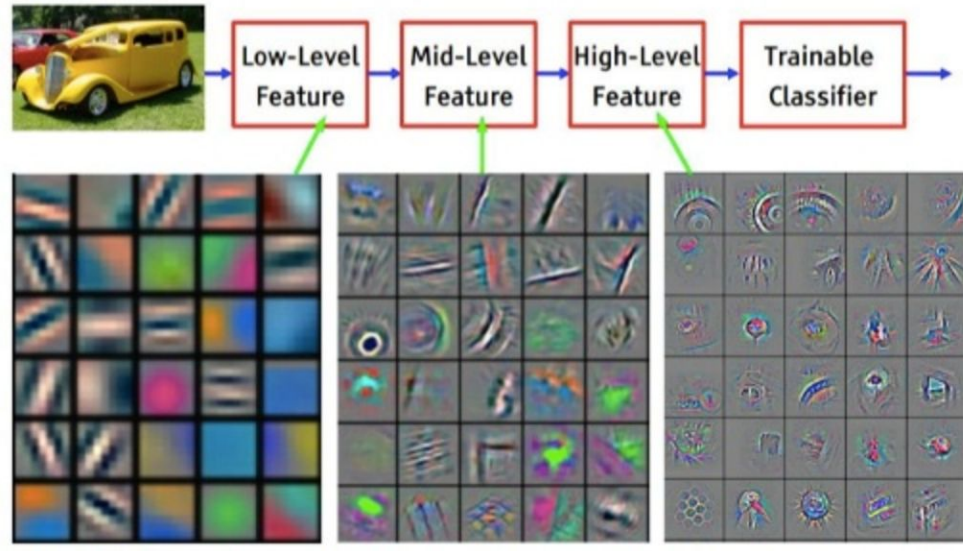# Adversarial Examples: a Generalization Failure?

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Chapter 1: The Dream
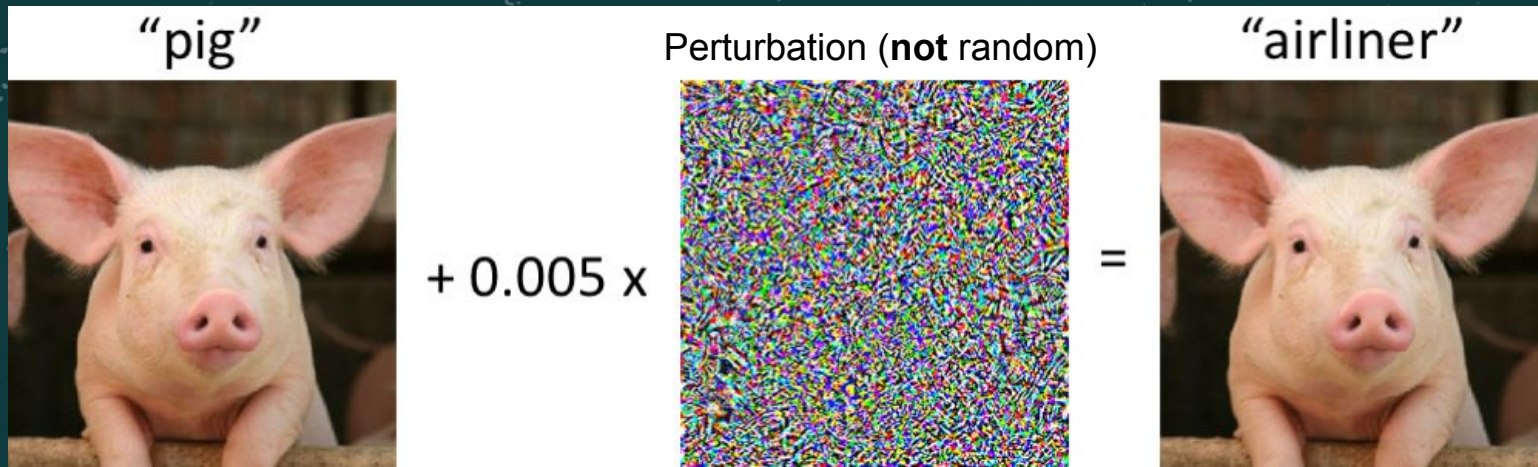
Chapter 2: The Bug

"Deep Learning can make pigs fly"

"pig"   Perturbation (**not** random)   "airliner"

+ 0.005 x   =

[szegedy et al. 2013]

Training set

dog ← Label

dog ← Model prediction

source:https://gradie...

Compute adv. Example

New training set

cat

cat

Train a Classif on that **bad train set**

??????

Normal Test Set !!!

dog

| | Std accuracy | Adv accuracy ($\varepsilon = 0.25$) |

Test Accuracy on $\mathcal{D}$ (%)

Std Training using $\mathcal{D}$ — Adv Training using $\mathcal{D}$ — Std Training using $\widehat{\mathcal{D}}_R$
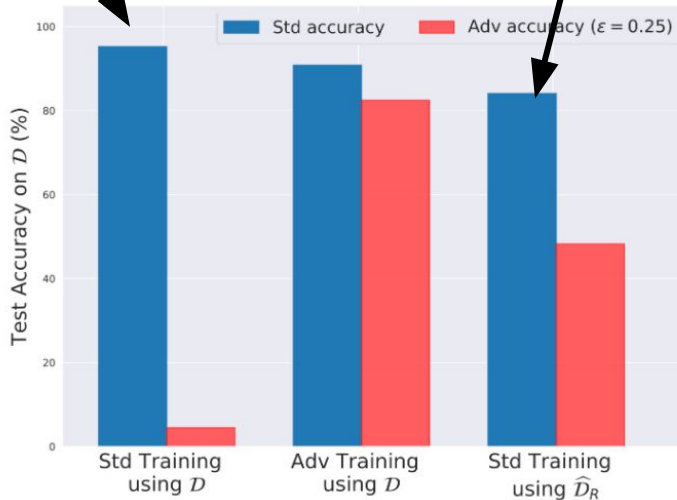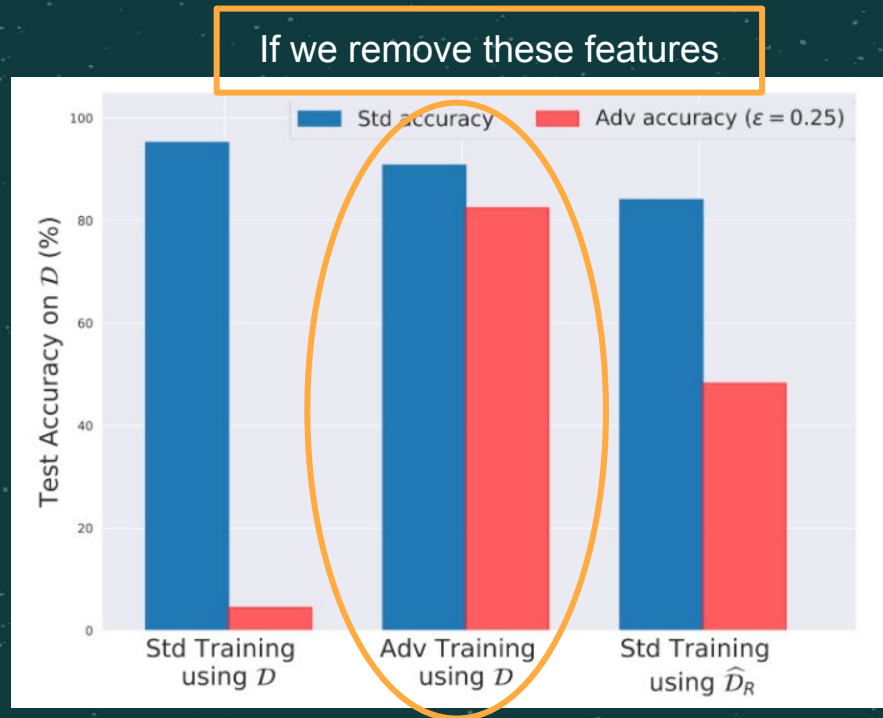
Chapter 3: The feature ???

[Ilya et al. 2019]

- These features are **useful** quantities for the prediction task.
- They **GENERALIZE** (in the sense of supervised learning)
- Adversarial Training remove these features.

If we remove these features

Chapter 4: the diagnosis

- Adversarial examples always exists
  [Bubeck, Cherapanamjeri, Gidel, Tachet des Combes 2021] [Daniely and Schacham 2020]

- Adversarial examples can be used for the **in-distribution Task.** [Ilyas et al 2019]

- **My Opinion:** there few hope that these feature will help for OoD generalization. (will learn them with standard supervised learning)

- Something is broken in standard supervised learning. (Adversarial examples are the symptom of that)

- First step of **OoD Generalization**: Robust models generalize to distributions "close" to the data distribution.

Conclusion

- In-distribution Generalization is a somewhat broken task. [Recht et al. 2018]
- Robustness (to adv examples) cannot help to that 'too easy task'
- Robustness can help is more challenging task (sub-population shift) [Santurkar et al. 2021] (to be proved that it can help for OoD in a broader sense)