Intelligence Artificielle Avancée (RCP211)
Robustesse décisionnelle
Stabilité et généralisation

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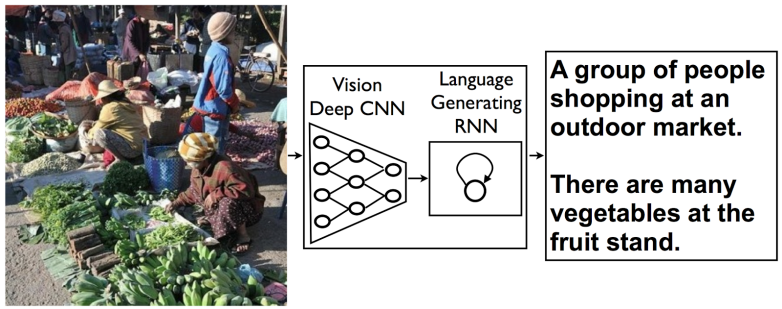
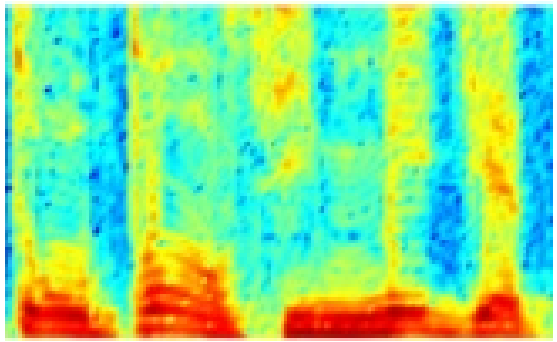
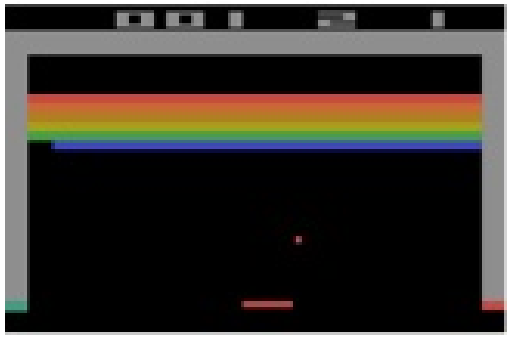
Outline

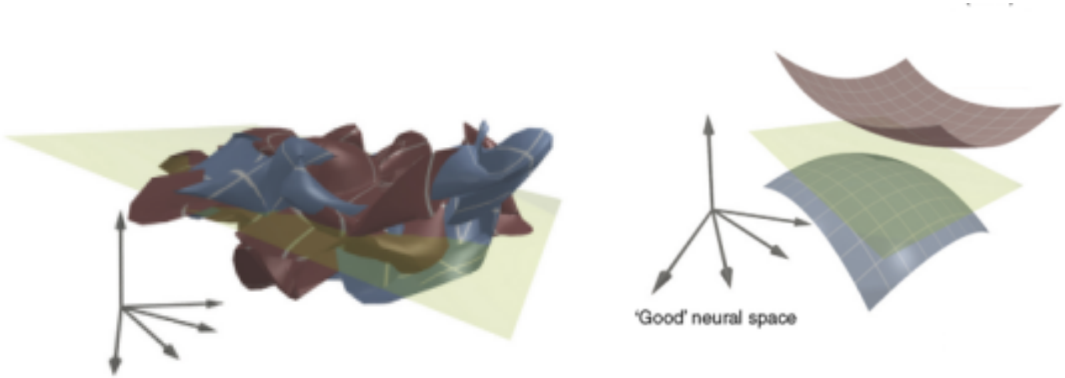
Deep Learning Theory





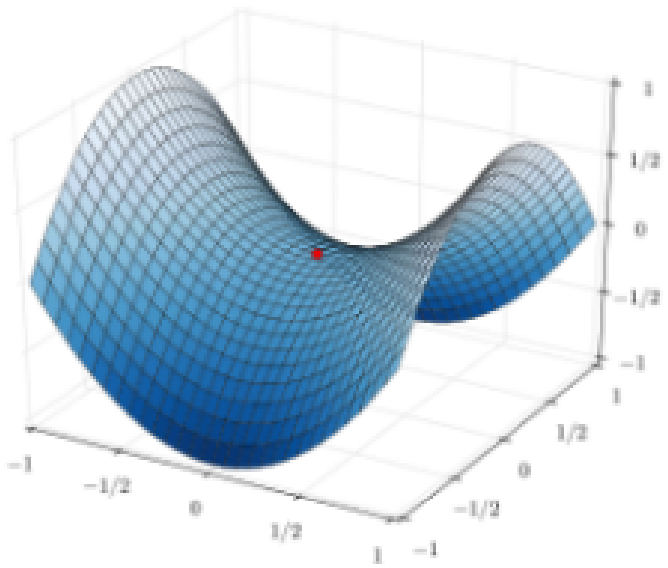


- Deep Learning: huge impact in terms of experimental results
- BUT: formal understanding still limited, other robustness issues
  - Optimization: non-convex problem
  - Generalization & over-fitting
  - Stability of the decision function
  - Explainability of the decision



Non-Convex Optimization

- One of the main historical shortcoming of deep neural networks
- In pratice, not really an issue with modern neural networks, WHY?
- Some preliminary answer elements:
  - In high dimension, few local minima
    but many saddle points [Dauphin et al., 2014]
    - Empirically, gradient descent methods manage to
      escape [Goodfellow and Vinyals, 2015] saddle points



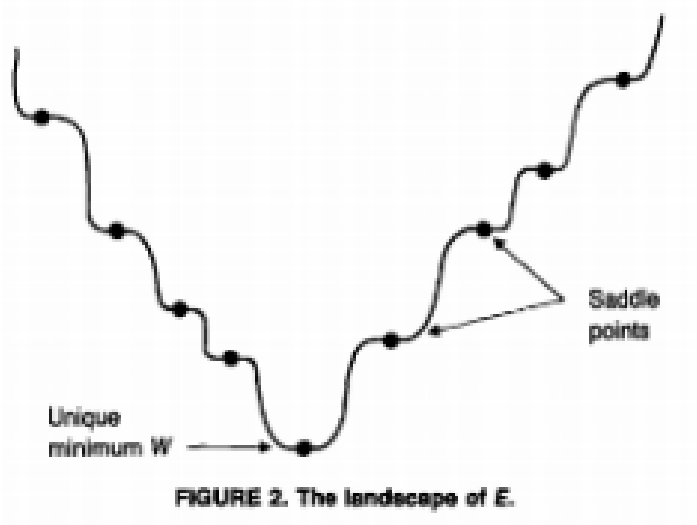
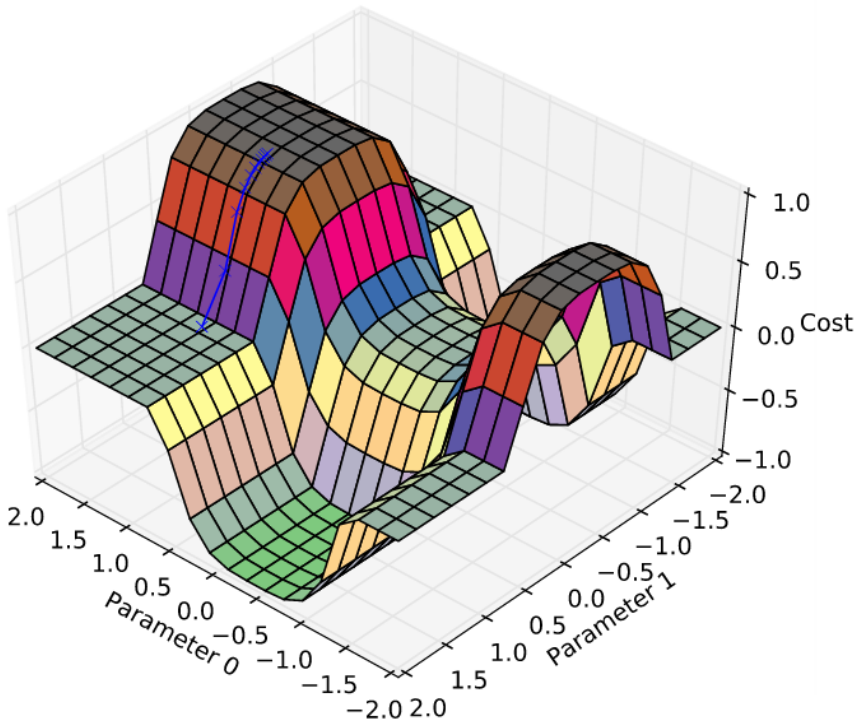


FIGURE 2. The landscape of E.

Non-Convex Optimization

- WHY non-convex optimization ist not a major practical issue for deep learning?
- Some preliminary answer elements:
  - Most of local minima have about the same objective value [Haeffele and Vidal, 2015, Choromanska et al., 2014]

(Cartoon of Dauphin et al 2014's worldview)

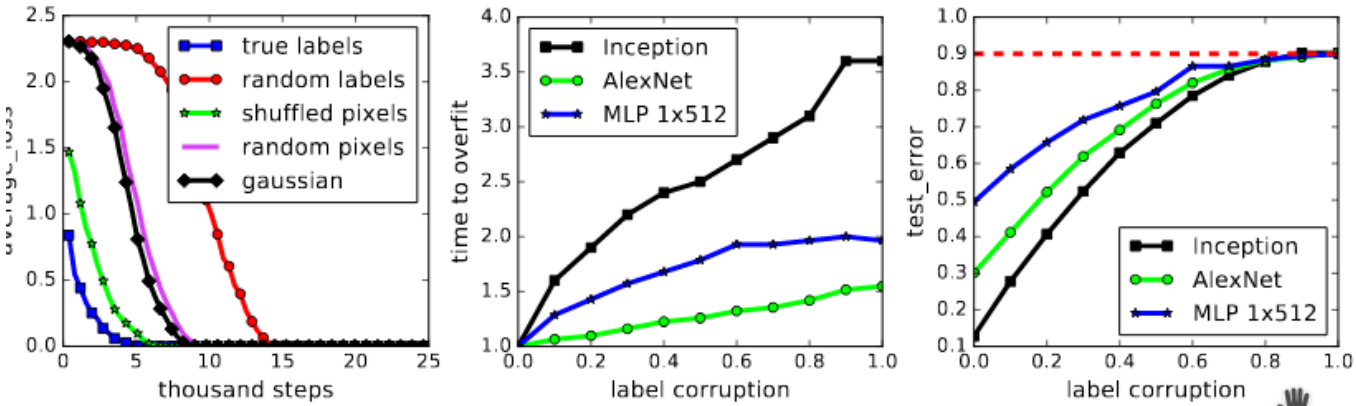


Deep Learning and generalization

- Rademacher complexity: capacity of a model to fit random label :

$$\mathcal{R}_n(\mathcal{H}) = E_\sigma \left[sup_{h \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^{n} \sigma_i h(x_i) \right]$$

- Rethinking generalization: Zhang *et. al.* ICLR17 [Zhang et al., 2017]



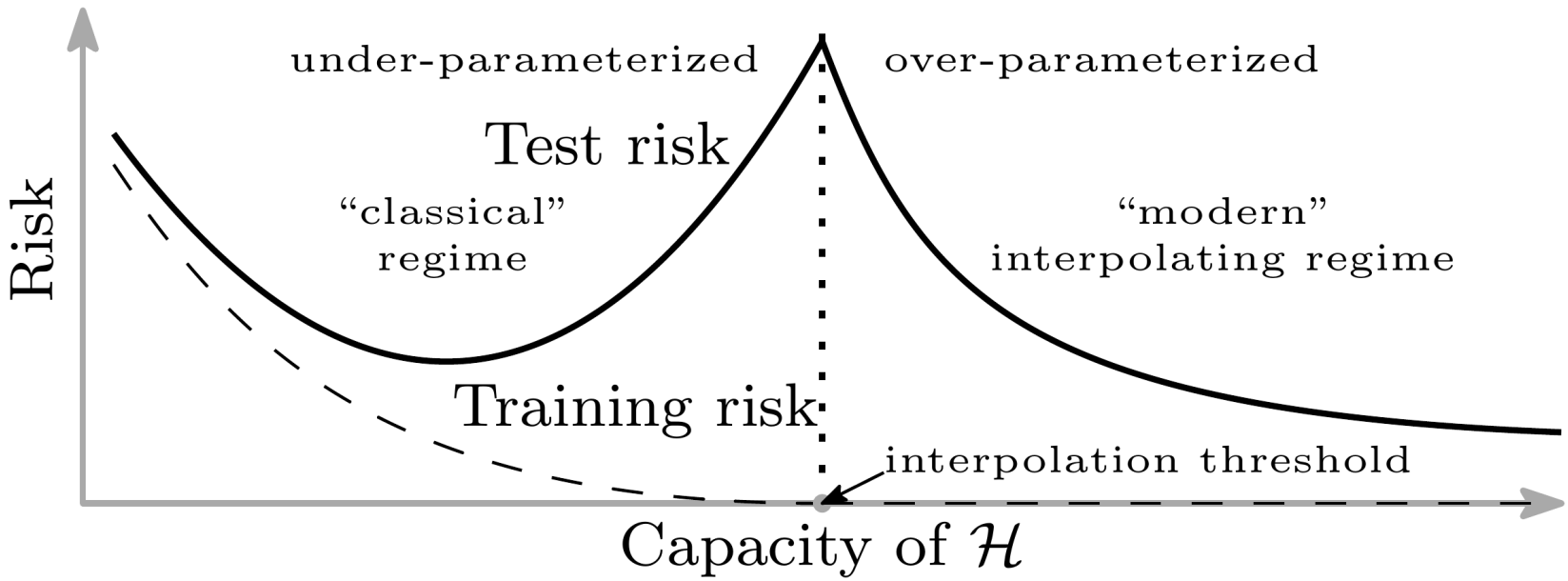
(a) learning curves (b) convergence slowdown (c) generalization error growth

  - Deep models easily fits random labels !!
  - $\mathcal{R}_n(\mathcal{H}) \approx 1 \Rightarrow$ no theoretical guarantee on generalization performances

- **Classical learning theory insufficient to explain the good generalization behavior of deep models**

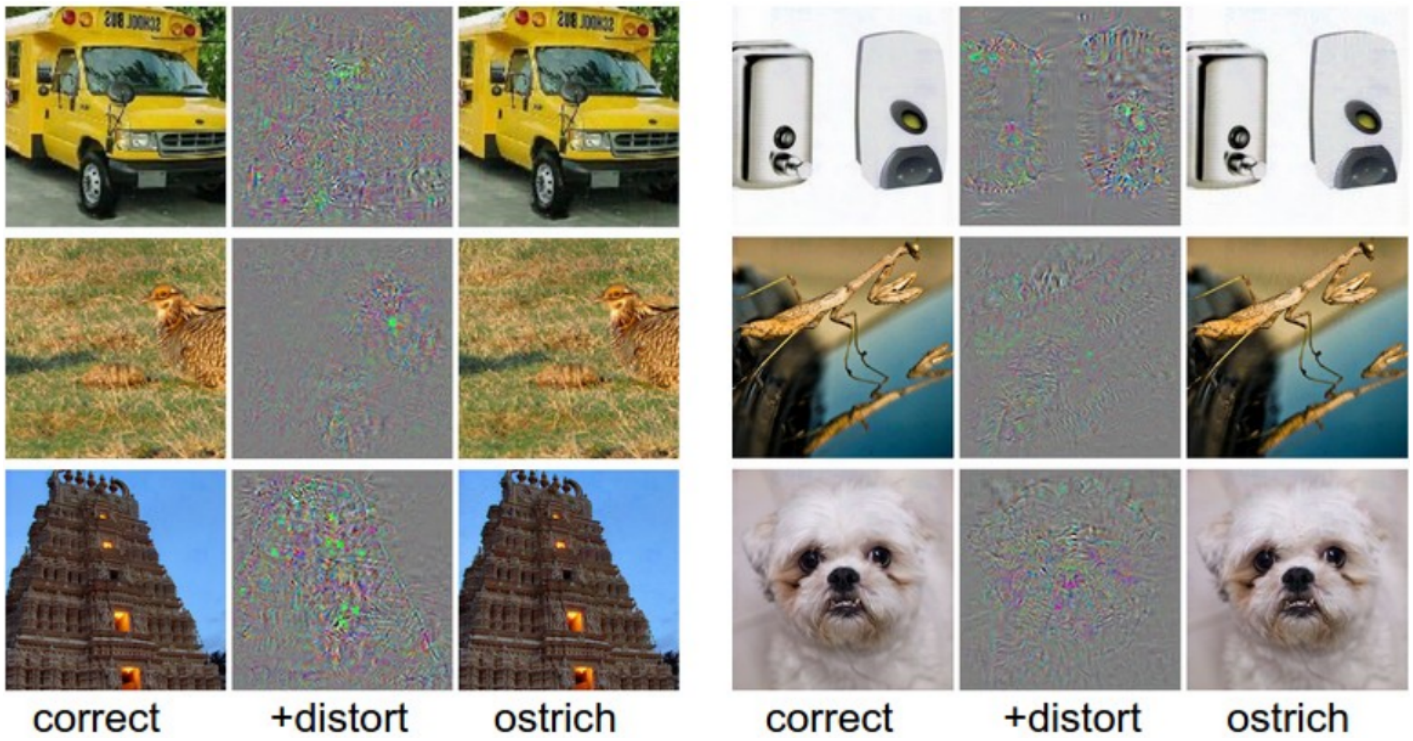
Generalization and over-parametrized models

- Double U-curve phenomena observed with deep models! [Belkin et al., 2019]



Deep Learning (DL) & Stability

- **Stability:** decision function with "controlled" variations
  - Small input variations $\Leftrightarrow$ reasonably small output variations on decision, *e.g.* Lipschitz property
  - **Decision function of deep Models not always stable**
    - **Ex: Adversarial Examples**



Deep Learning (DL) & Stability

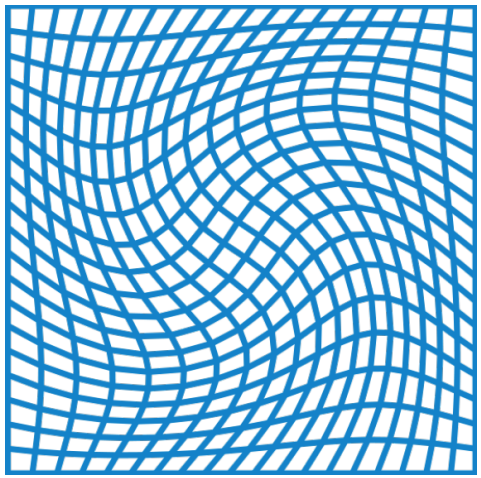
- Adversarial attacks in real-world

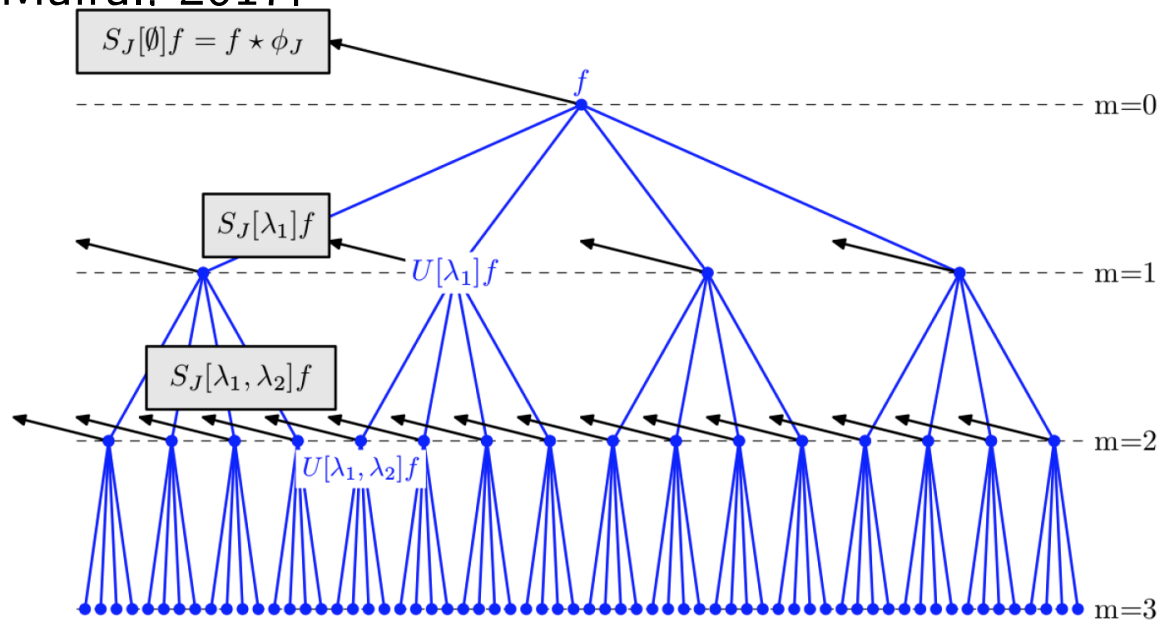
[Evtimov et al., 2017]

Deep Learning (DL) & Stability

Formal stability analysis of deep models

- Harmonic analysis in scattering operators [Mallat, 2012, Bruna and Mallat, 2013], *i.e.* "deep wavelets"
  - Show stability / invariance to diffeomorphisms
  - Stability bounds
- Generalized to deep kernel machines, closer to SoTA deep ConvNet architectures [Bietti and Mairal, 2017]

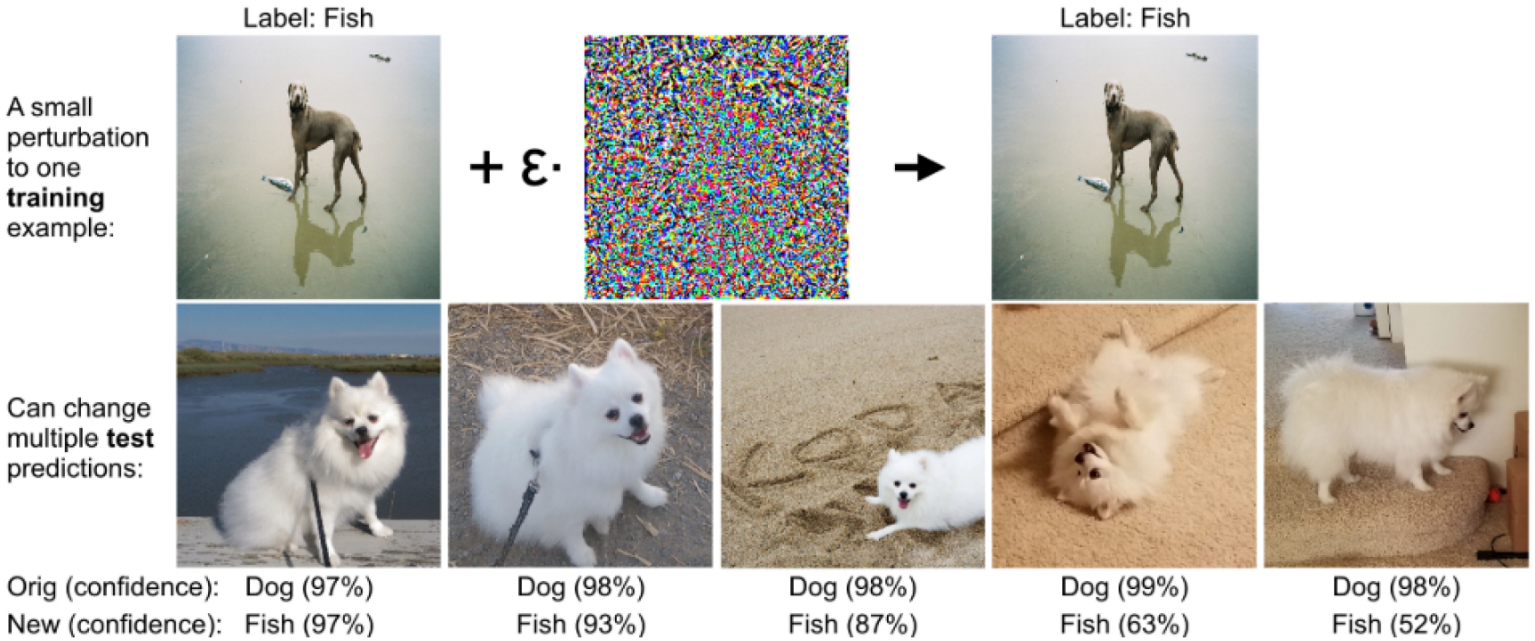




Deep Learning (DL) & Stability

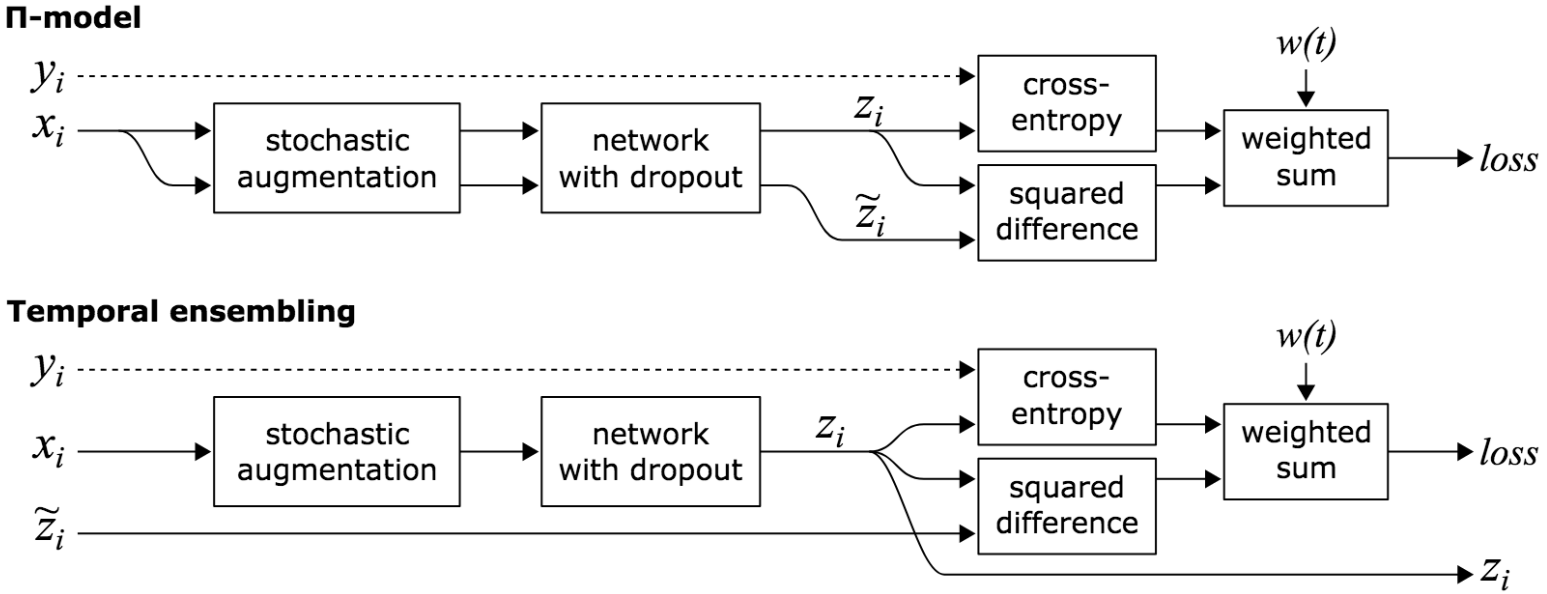
Formal stability analysis of deep models

- Influence Functions [Cook and Weisberg, 1980]
  - Characterize decision function influence on training examples
    - Removing a training point: $\mathcal{I}_{up,loss}(z, z_{test}) = -\nabla_\theta L(z_{test}, \hat{\theta})^T H_\theta^{-1} \nabla_\theta L(z, \hat{\theta})$
    - Perturbing it: $\mathcal{I}_{pert,loss}(z, z_{test})^T = -\nabla_\theta L(z_{test}, \hat{\theta})^T H_\theta^{-1} \nabla_x \nabla_\theta L(z, \hat{\theta})$
  - Adapted / applied to deep networks [Koh and Liang, 2017]
- Data poisoning



Ad hoc stability training

- Regularization criterion supporting learning stable decision function
  - Underlying model might not be stable, but helps to focus on a subet of stable functions of the family
- Robustness of the decision to transformations [Sajjadi et al., 2016], stability accross iterations [Laine and Aila. 2017. Tarvainen and Valpola. 2017]



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Understanding deep learning requires rethinking generalization.