

# Synthesizing Robust Adversarial Examples

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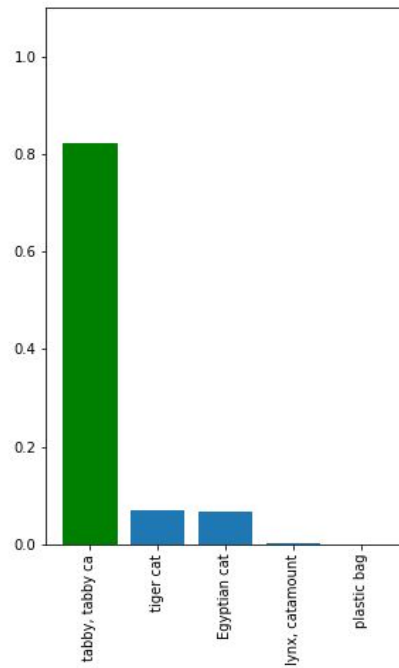
# Standard Adversarial Examples

**Given** image  $x$ ; target class  $y$

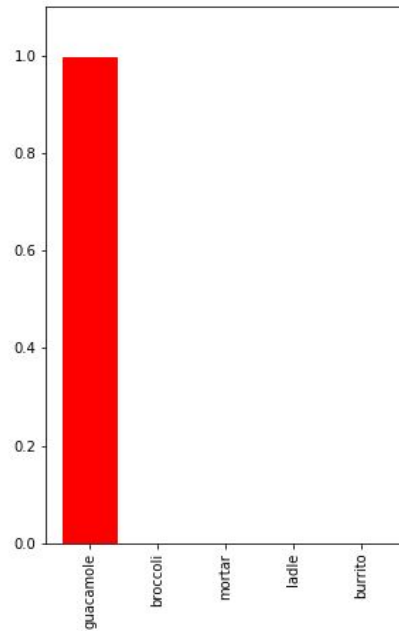
**Maximize** with projected gradient descent:

$$x_{adv} = \arg \max_x P(y|x) \quad \text{s.t. } d(x, x_0) < \epsilon$$

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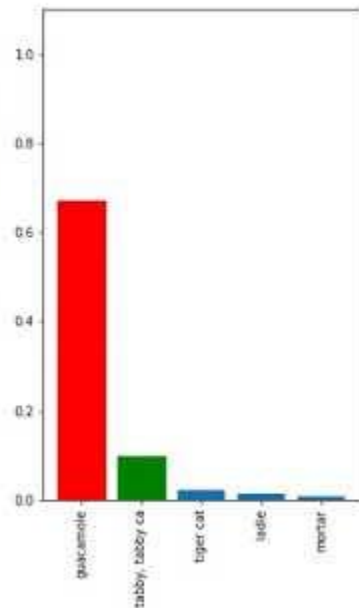
**Maximize** with projected gradient descent:

$$x_{adv} = \arg \max_x P(y|x) \quad \text{s.t. } d(x, x_0) < \epsilon$$

What happens when we transform the images?

# Standard Examples are Fragile

Zoom: 1.001494x



# Robust Adversarial Examples

**Given** image  $x$ ; target class  $y$ ; distribution of transformations  $T$

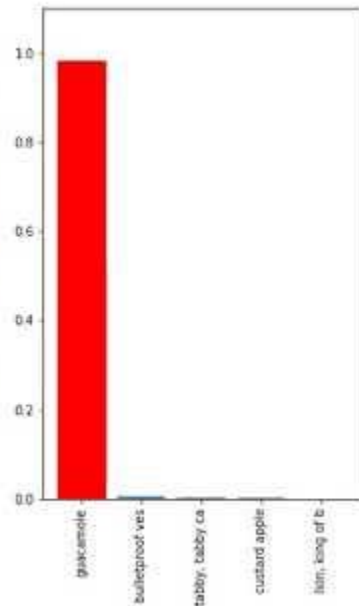
Maximize expectation over transformation:

$$x_{adv} = \arg \max_x \mathbb{E}_{t \sim T} [P(y|t(x))] \quad \text{s.t. } d(x, x_0) < \epsilon$$

What happens when we transform the images?

# Robust Adversarial Examples

Zoom: 2.804511x





# Implementation

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Euclidean LAB distance:

$$d(x, x_0) := \mathbb{E}_{t \sim T} \|\text{LAB}(t(x)) - \text{LAB}(t(x_0))\|_2$$

Lagrangian Relaxation:

$$\hat{x} = \arg \min_{x'} \mathbb{E}_{t \sim T} [-\log P(y|t(x')) + \lambda \|\text{LAB}(t(x)) - \text{LAB}(t(x'))\|_2^2]$$

Law of Large Numbers:

$$\mathbb{E}_{t \sim T} [P(y|t(x))] \approx \frac{1}{N} \sum_{t_i \sim T} P(y|t_i(x))$$

$$\mathbb{E}_{t \sim T} [\|t(x) - t(x_0)\|] \approx \frac{1}{N} \sum_{t_i \sim T} \|t_i(x) - t_i(x_0)\|$$

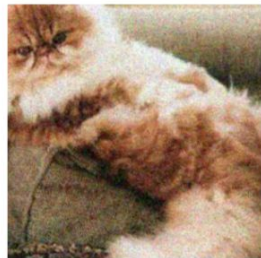
# Results



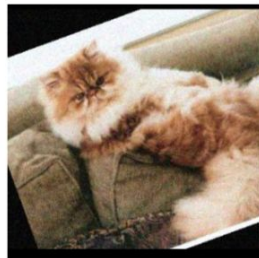
Original: Persian  
cat



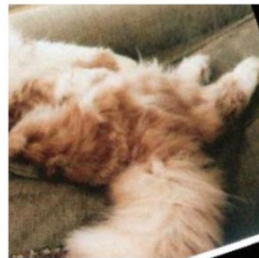
Adversarial:  
jacamar  
 $\ell_2 = 2.1 \times 10^{-1}$



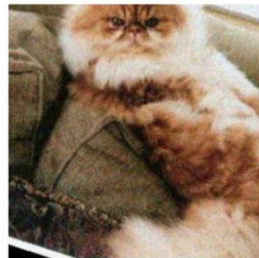
$P(\text{true}): 97\%$   
 $P(\text{adv}): 0\%$



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 $P(\text{adv}): 0\%$



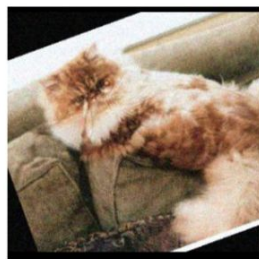
$P(\text{true}): 19\%$   
 $P(\text{adv}): 0\%$



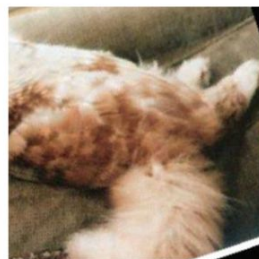
$P(\text{true}): 95\%$   
 $P(\text{adv}): 0\%$



$P(\text{true}): 0\%$   
 $P(\text{adv}): 91\%$



$P(\text{true}): 0\%$   
 $P(\text{adv}): 96\%$



$P(\text{true}): 0\%$   
 $P(\text{adv}): 83\%$



$P(\text{true}): 0\%$   
 $P(\text{adv}): 97\%$

# Scaling EOT to 3D

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Bundle everything into the transformation:

- 3D rendering
- 3D rotation
- Perspective projection
- Lighting
- Noise





# Challenges

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- Implementing a differentiable renderer
- Modeling 3D printer color inaccuracy
- Approximating physical phenomena
- Choosing parameters of distribution





# Demo

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