Effectiveness of adversarial examples on convolutional neural networks

Presented by

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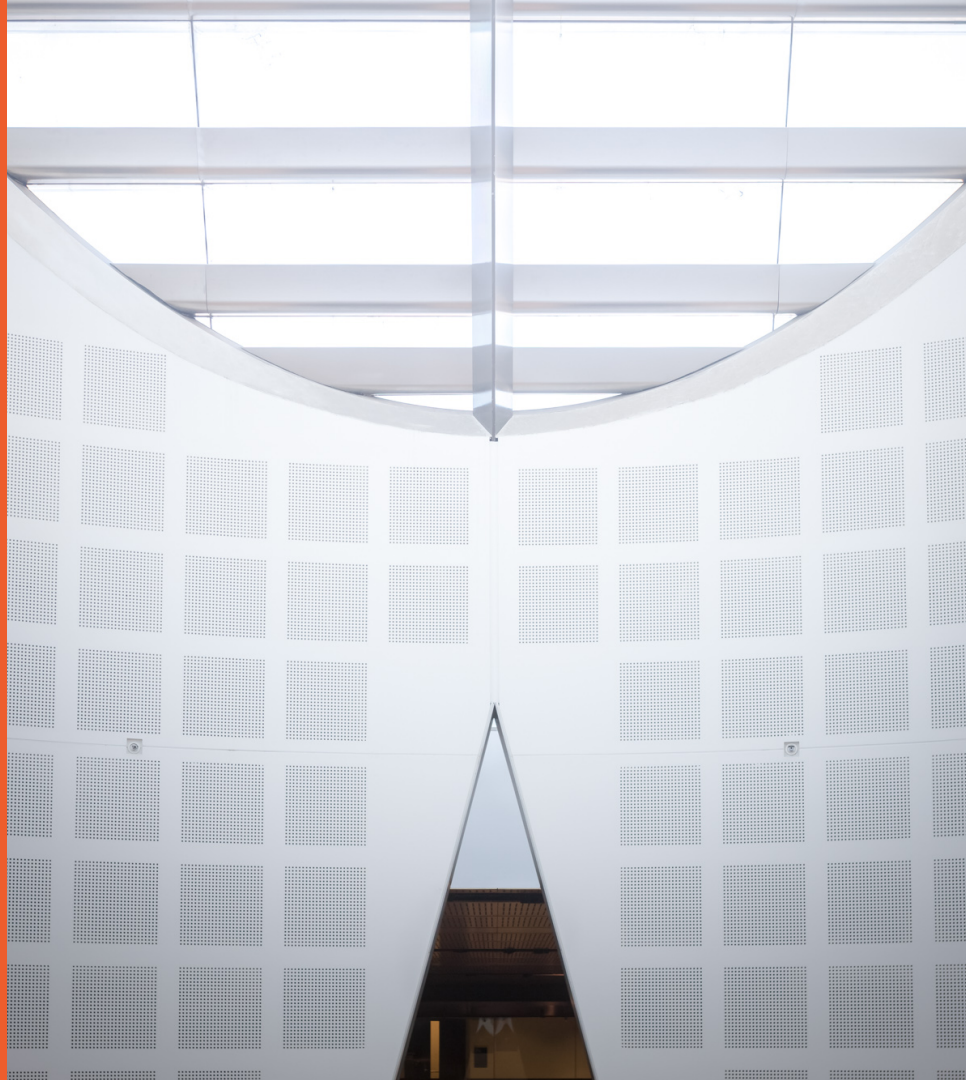

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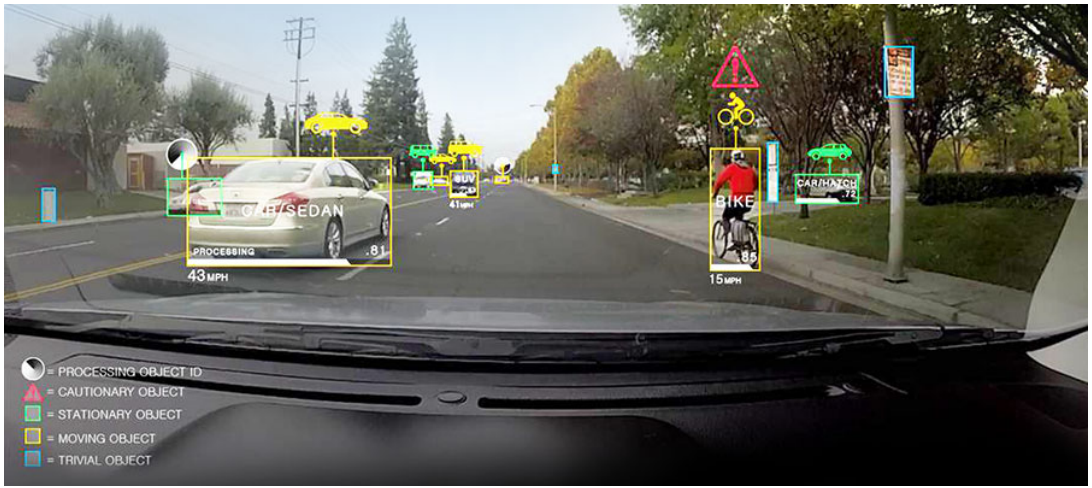
What is Computer vision?

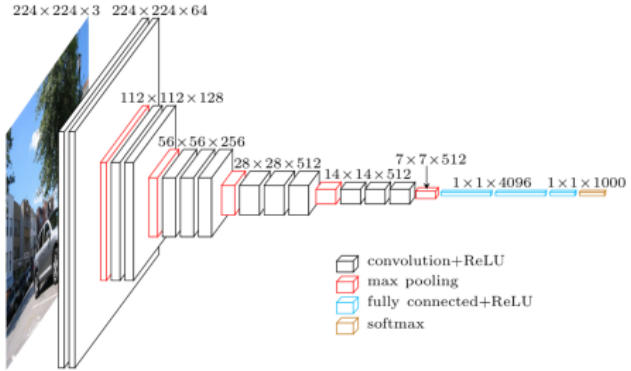
- *" Computer vision is an interdisciplinary field that deals with how computers can be made to gain high-level understanding from digital images or videos"* - Wikipedia



Example of object segmentation on a self-driving car [1]

Convolutional neural networks

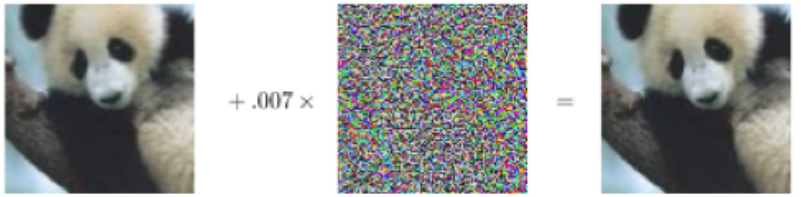
- "Type of feed-forward neural network which the connectivity pattern is inspired by the organization of the animal visual cortex" [2]
- It provides state of the art performance on data with spatial structure [1].



An example of CNN architecture, VGGNet [3]

Adversarial inputs

- Intentional modification on inputs to deliberately yield erroneous model outputs, while appearing unmodified to human observers.
- Depend on model information to successfully generate an adversary



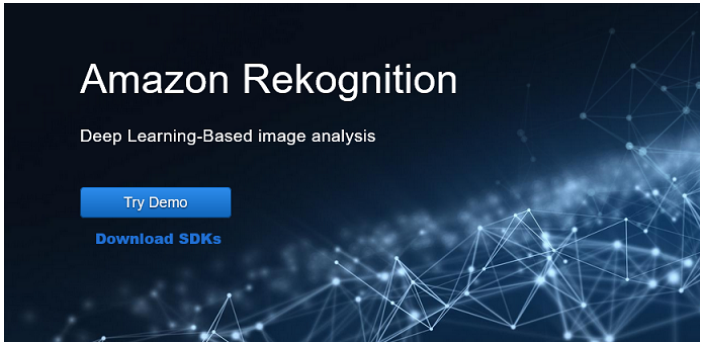
Adversarial crafting using Gradient Sign from Goodfellow et al. (2014) [3]

Imbalanced learning and domain shift

- **Imbalanced Learning**: When the underlying training set contains high variance on the number of samples for each class.
- **Domain Shift:** When the joint distributions of inputs and outputs differs between training and test stages.

Motivation

- Image recognition systems have been used widely in commercial applications
- Adversarial attacks are proven to work on state of the art convolutional neural networks (CNNs) architectures.
- Real world data is often imbalanced with lots of missing values
- There is no empirical evidence of adversarial attacks on class-imbalanced CNNs



Research question

- Would adversarial attacks be more effective on networks trained on Imbalanced datasets?
  - Does the attacks heavily depend on the targeted model internal knowledge?
  - Does classes with similar and different features space behave equally to adversarial attacks?

Contributions

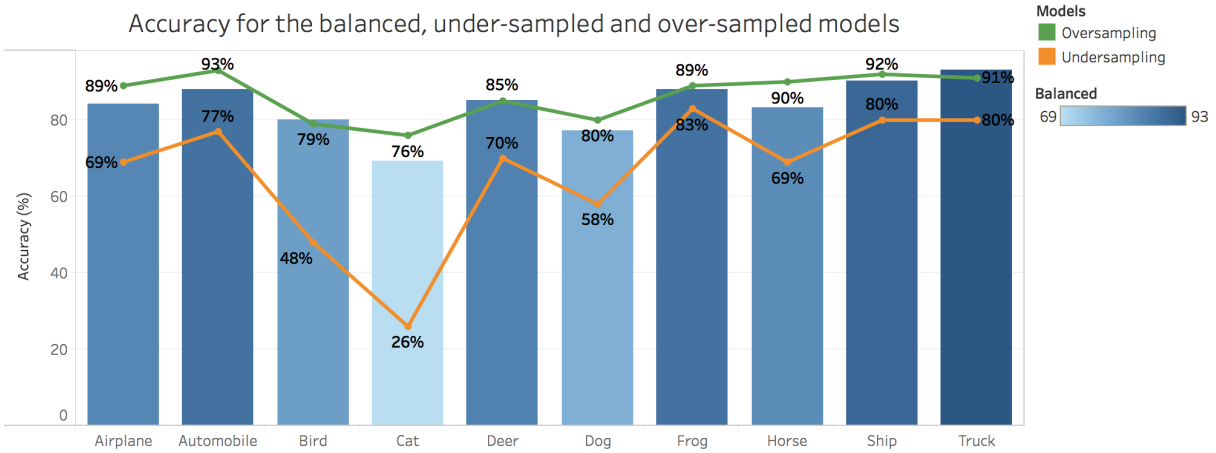
- Evaluation of the resilience of imbalanced CNNs to adversarial attacks using the white-box and black-box approach
- Investigation of classes with overlapping distributions and their relationship to both adversarial attacks and imbalanced learning problem

Experiment design (1): CNN Architecture

- First architecture to show that the depth of a network its critical to its performance
- Homogeneous architecture: Only 3x3 convolutions and 2x2 pooling from beginning to end
- We've changed the architecture to cope with the smaller input size (32x32).
- **Change**: Two 4096 FC => single 512 FC layer
- **Change**: 3 Convolution/pooling blocks instead of 4.

Experiment design (2): Imbalanced dataset

- **CIFAR-10**, 32x32 images on 10 non-hierarchical classes, 60,000 samples
- **Modified VGG**: achieved 83% overall accuracy on the balanced dataset
- **Baseline**: Balanced dataset vulnerability to adversaries
- **Tests**: 20 different imbalanced variations with under-sample and over-sample on each of the 10 classes



Experiment design (3): Gradient sign method

$$C(x+\delta) \approx C(x) + \epsilon * sign(\nabla C)$$
$$C(x+\delta) \approx C(x) - \epsilon * sign(\nabla C)$$

- Uses the gradient of any chosen class to add small noise to image pixels
- Only the gradient direction is used due to the ***sign*** operation, the magnitude of the perturbation is controlled by the **epsilon**
- Fast gradient sign x Iterative gradient sign
- Ascent x Descent perturbations
- **Epsilon 0.01**: Best trade-off between misclassification and image noise
- **Methods**: Fast gradient sign and ascent perturbations
- **Backpropagated gradient**: True class
- **Intuition**: Increase the cost function of the true class by the **epsilon** value in all gradient directions

Experiment design (4): White/Black-box attacks

- **Same model gradient (White-box):** Uses the underlying model knowledge to create optimal perturbations
- **Different model gradient (Black-box):** Uses an approximation of the true model, in this experiment, represented by the balanced network.
- Same data domain but datasets vary on the total number of samples.

Experiment workflow

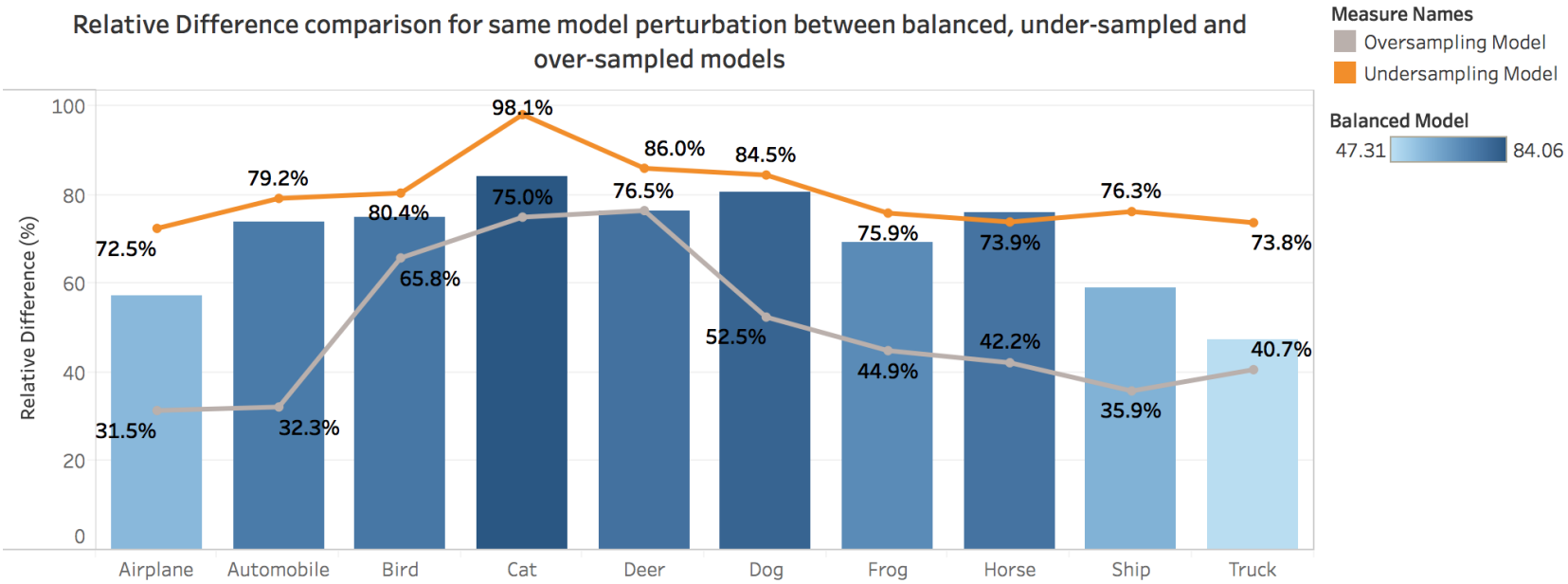
Results (1): Overall accuracy

- While the over-sampled models were more robust to adversaries, the under-sampled models had lower overall accuracy
- White-box attacks were generally more efficient than black-box attacks

	Black-box		White-box		
Class Label	Undersample	Oversample	Balanced	Undersample	Oversample
0 - Airplane	60%	87%	36%	19%	61%
1 - Automobile	64%	91%	23%	16%	63%
2 - Bird	38%	73%	20%	9.4%	27%
3 - Cat	21%	72%	11%	0.5%	19%
4 - Deer	58%	80%	20%	9.8%	20%
5 - Dog	47%	76%	15%	9%	38%
6 - Frog	76%	88%	27%	20%	49%
7 - Horse	59%	88%	20%	18%	52%
8 - Ship	69%	89%	37%	19%	59%
9 - Truck	46%	87%	49%	21%	54%

Results (2): Relative difference on white-box attacks

- We calculated the percentage difference between the non-perturbed and perturbed model – the graph shows the results for the 3 variations on the white-box attack



Results (3): Overlapping distributions

Classes with similar features are often misclassified as one another

Stronger Classes

Balanced dataset with white-box attack

	Airplane	Automobile	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Dog	0.024	0.006	0.18	0.38	0.086	0.15	0.068	0.059	0.013	0.032

Dog under-sampling with white-box attack

	Airplane	Automobile	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Dog	0.025	0.01	0.17	0.32	0.12	0.09	0.12	0.1	0.01	0.033

Balanced dataset with white-box attack

	Airplane	Automobile	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Automobile	0.025	0.23	0.013	0.013	0	0.004	0.015	0.001	0.03	0.67

Automobile under-sampling with white-box attack

	Airplane	Automobile	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Automobile	0.068	0.16	0.01	0.014	0.016	0.007	0.026	0.016	0.18	0.51

Weaker Classes

Balanced dataset with white-box attack

	Airplane	Automobile	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Cat	0.035	0.005	0.15	0.11	0.12	0.31	0.14	0.045	0.026	0.06

Cat under-sampling with white-box attack

	Airplane	Automobile	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Cat	0.038	0.006	0.14	0.005	0.15	0.39	0.13	0.085	0.038	0.031

Balanced dataset with white-box attack

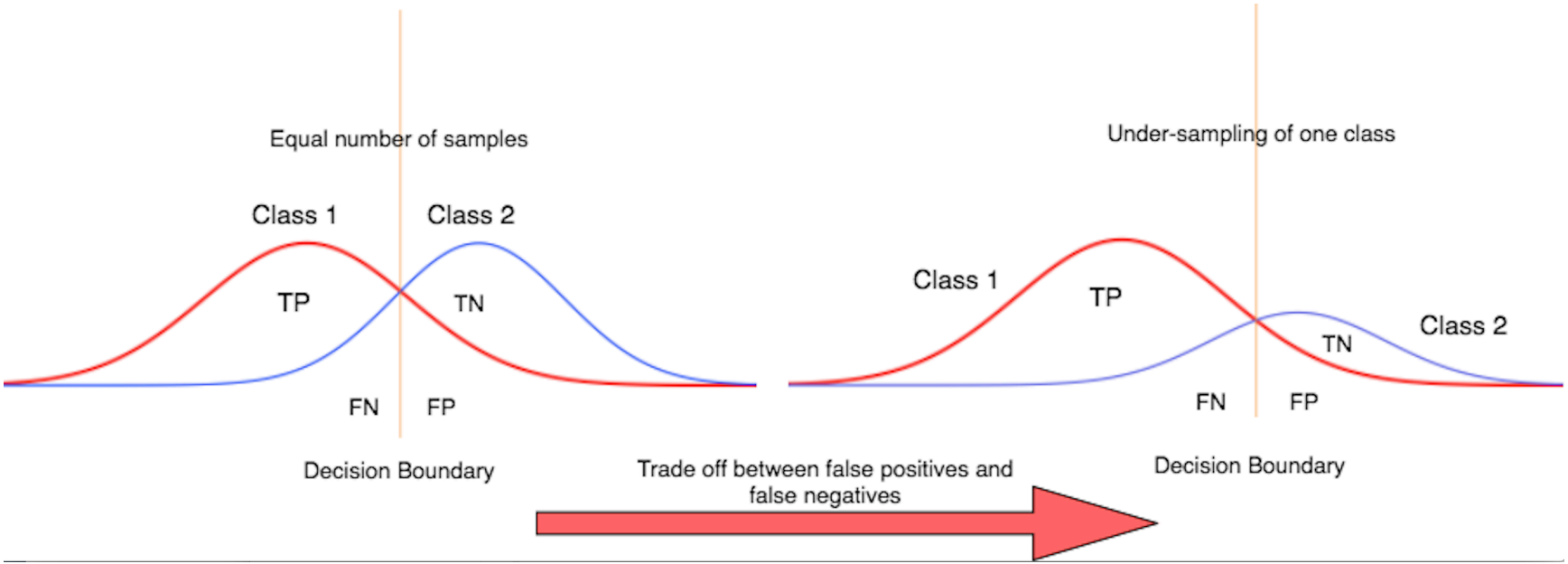
	Airplane	Automobile	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Truck	0.084	0.23	0.032	0.03	0.018	0.019	0.012	0.015	0.065	0.49

Truck under-sampling with white-box attack

	Airplane	Automobile	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck
Truck	0.11	0.42	0.022	0.043	0.038	0.01	0.023	0.039	0.089	0.21

Results (4): Decision boundary bias

Data imbalance causes a natural trade-off between over-sampled and under-sampled labels



Conclusions

- Under-sampled networks are more vulnerable to adversarial attacks while over-sampling increase robustness
- Black-box attacks are less effective than white-box which shows that gradients learned differs greatly even if we use the same data domain
- On the white-box attack with under-sampled training set, the non-dominant class was misclassified more often as the dominant class (overlapping distributions).
- CNNs shows linear behavior in high-dimensional spaces

Future Work?

- Use datasets with more classes
- Try different gradient sign methods with different combinations of epsilon values
- Do adversarial attacks are less or more vulnerable on different CNNs architectures?

Questions?