Advances in Deep Learning

by Wojciech Zaremba

Ex-Intern at

Grad student at

Intern at Google Brain

Outline

- Success stories
- Neural networks
- Convolutional neural networks
- Recurrent neural networks
- Flaws

House Number Identification in Street View*

*“Multi-digit Number Recognition from Street View Imagery using Deep Convolutional Neural Networks“ by Ian J. Goodfellow, Yaroslav Bulatov, Julian Ibarz, Sacha Arnoud, Vinay Shet

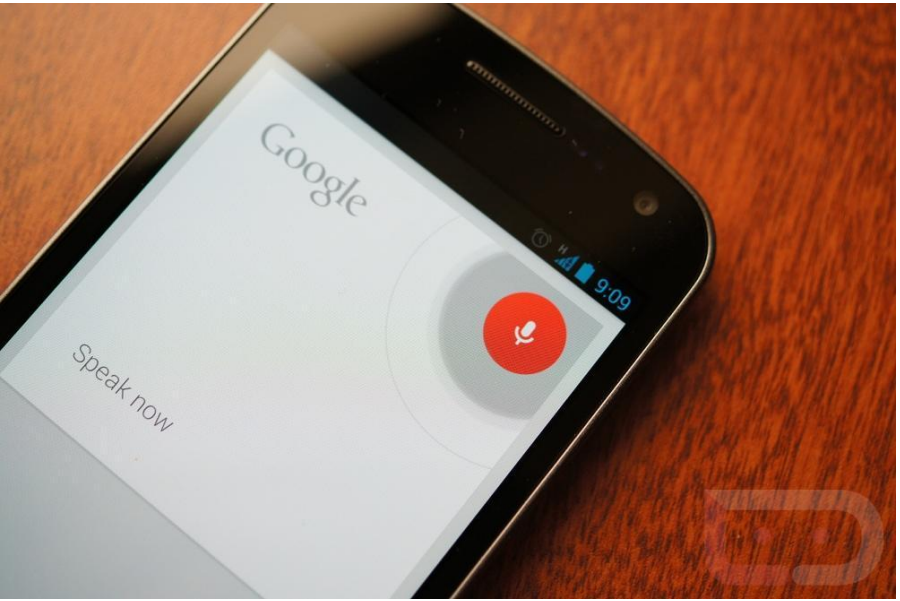
Image Classification (query animal)

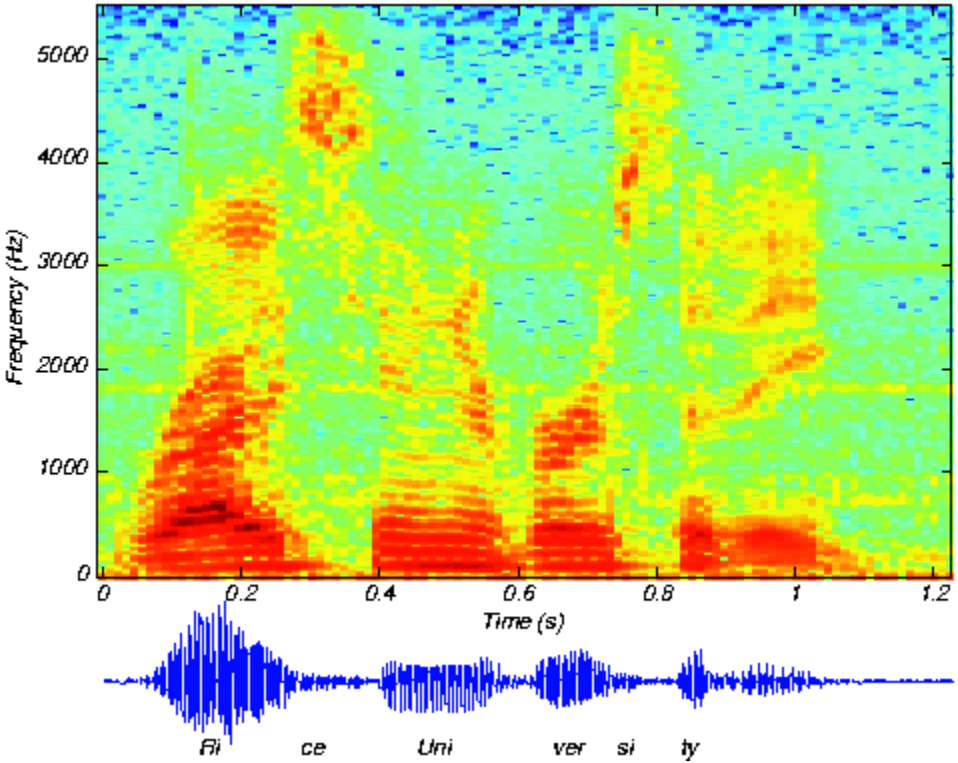
ImageNet classification results

1M training images, 1K categories, top-5 error

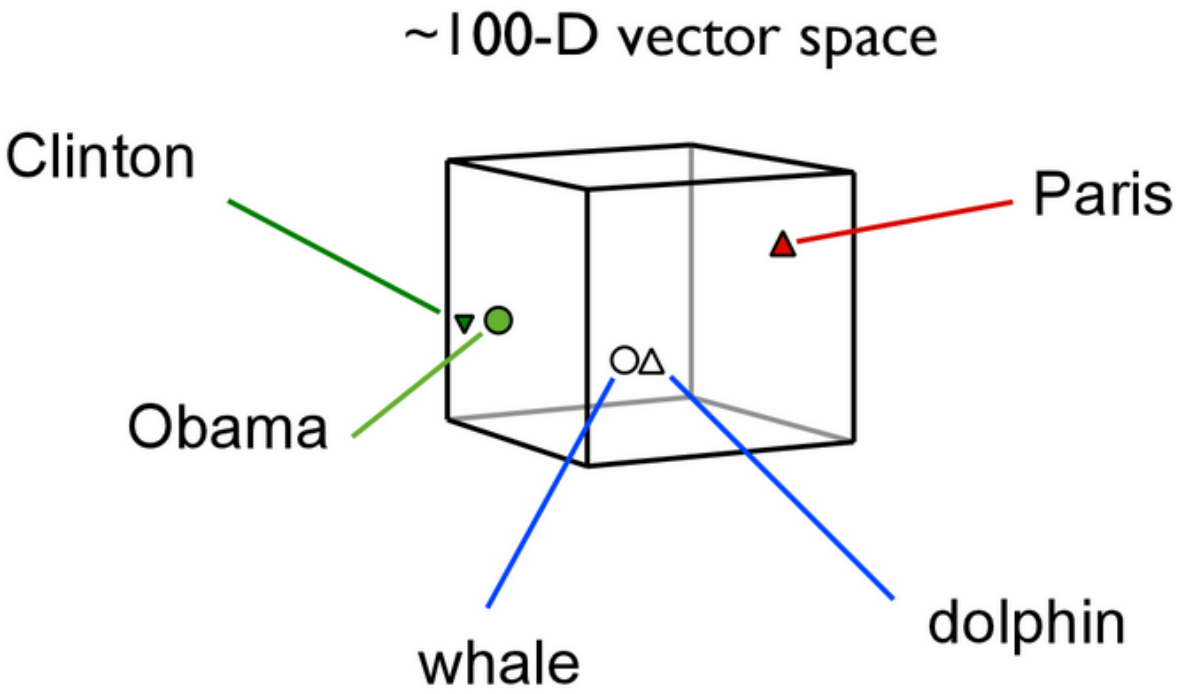
Best deep-learning models	~9%
Non-deep learning models ISI, Japan Oxford, England INRIA, France University of Amsterdam, etc.	~26%

Speech recognition



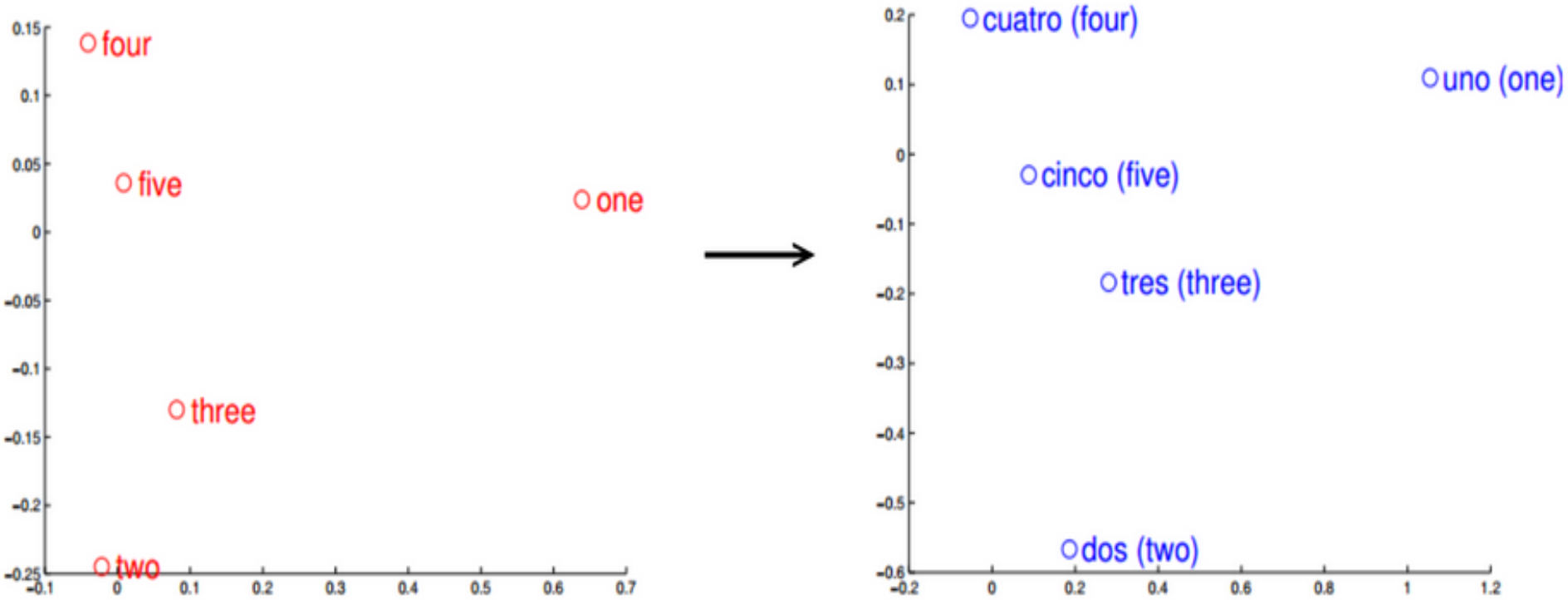


Text understanding*



*"Efficient estimation of word representations in vector space" by Tomas Mikolov, Kai Chen, Greg Corrado, Jeffrey Dean

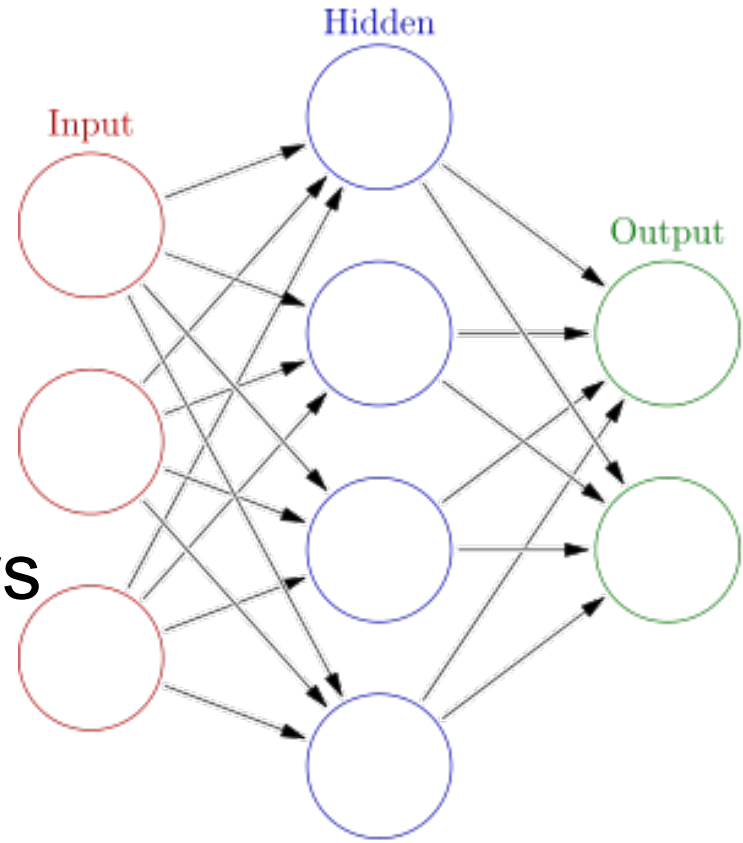
Translation*



*"Exploiting similarities among languages for machine translation" by Tomas Mikolov, Quoc V Le, Ilya Sutskever

Neural networks

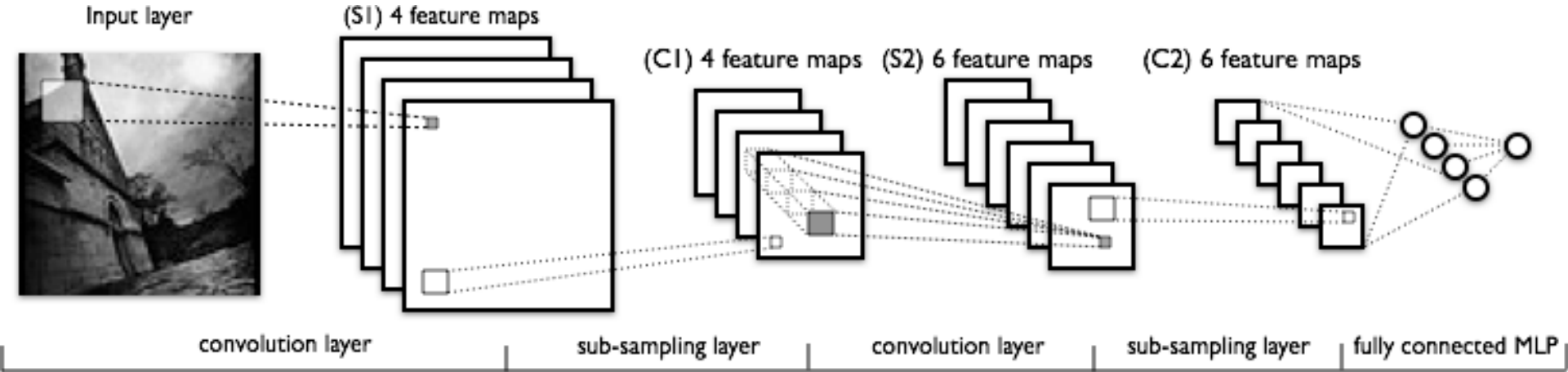
- Depth is essential for good performance
- Large amount of data shows their power
- Success due to fast GPUs



Convolutional neural networks

Assumptions:

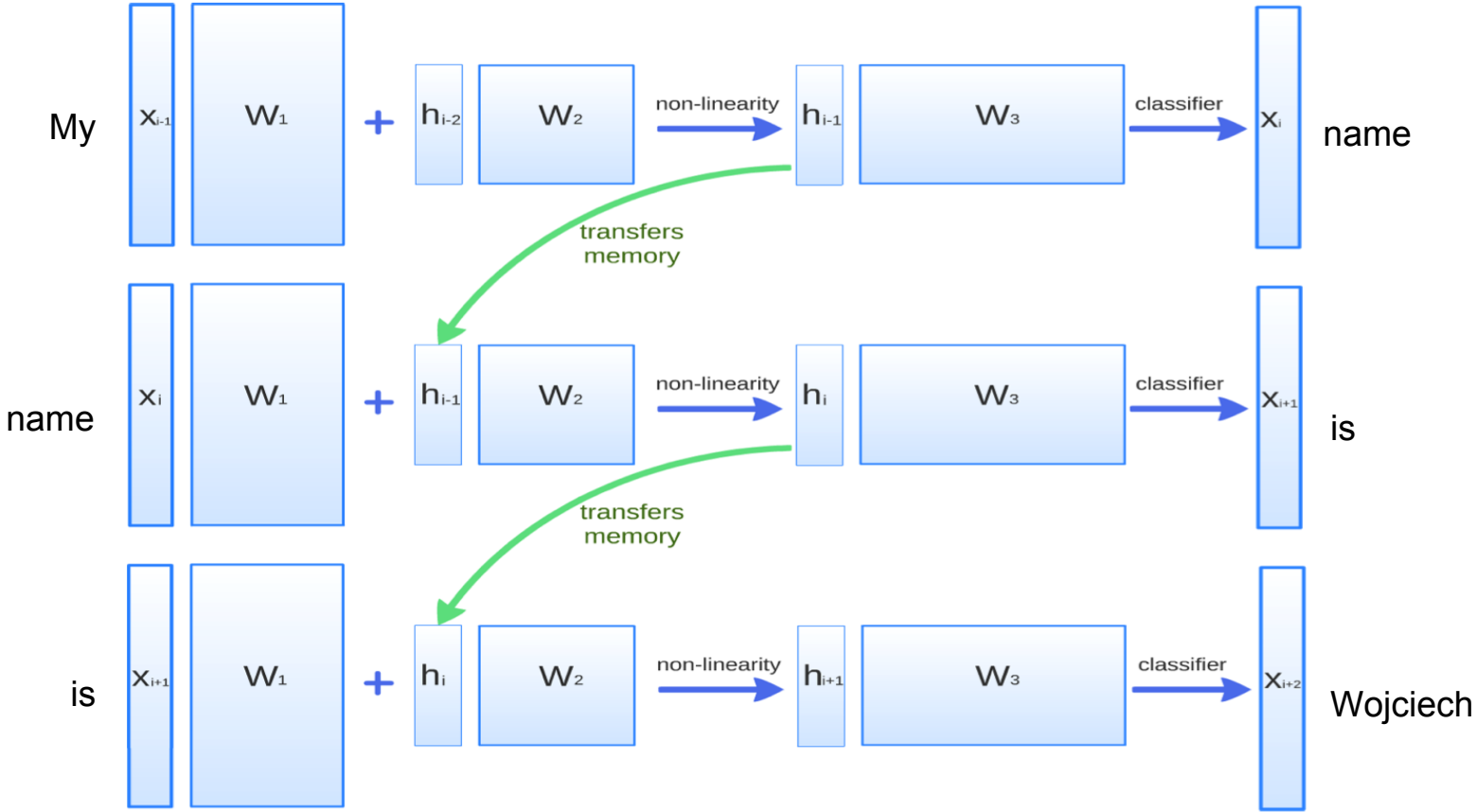
- on the very small scale every piece of image should be processed the same way



Convolutional networks - setting

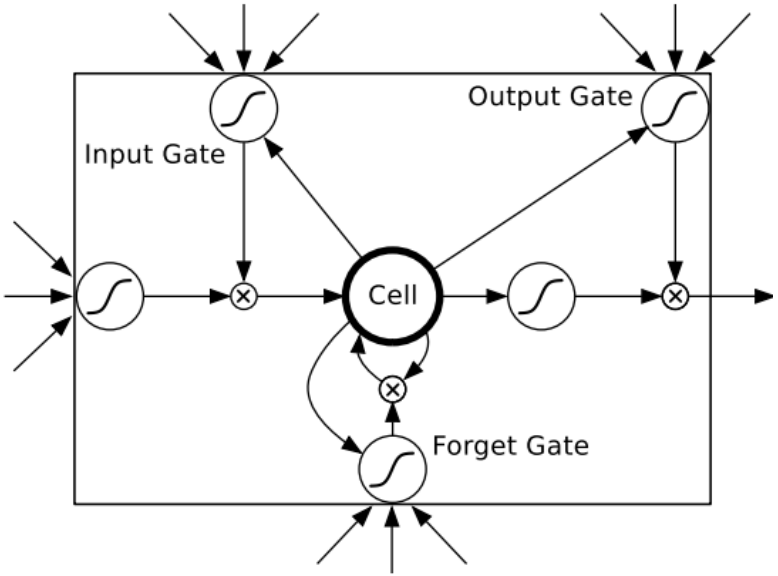
- 60 million parameters
- Training takes ~5 days on GTX Titan
- ~90% time takes convolutions, and ~10% time fully connected
- ~5% of parameters are in convolutions and ~95% of parameters in fully connected layers

Recurrent neural networks - schema



Long-short-term memory (LSTM)

- Variant of RNN
- Differentiable memory unit
- Equivalent to RNN but easier to train



Language modeling (Penn tree bank)

Model	**Perplexity** **(lower is better)**
Previous state of the art	73
Our result	68

Recurrent networks - applications

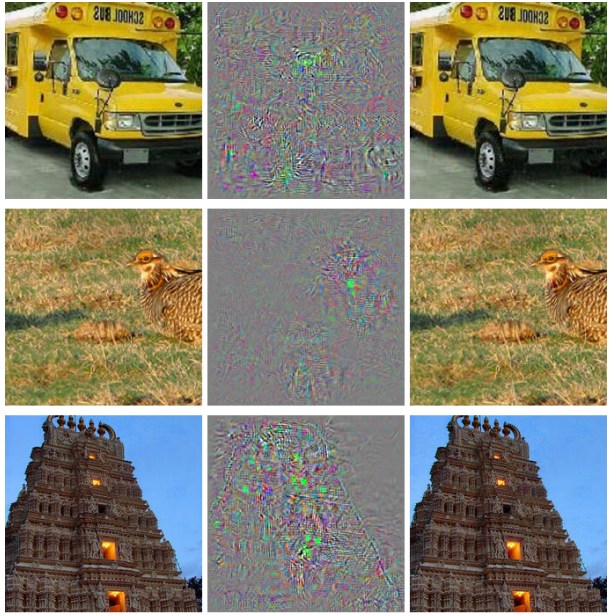
- Text understanding
- Video modeling thought consecutive frame prediction
- Translation
- Speech recognition
- Autocompletion

Recurrent neural networks

The meaning of life is
the tradition of the
ancient human
reproduction: it is
less favorable to the
good boy for when to
remove her bigger.

Flaws*

Correctly predicted object



Predicts ostrich

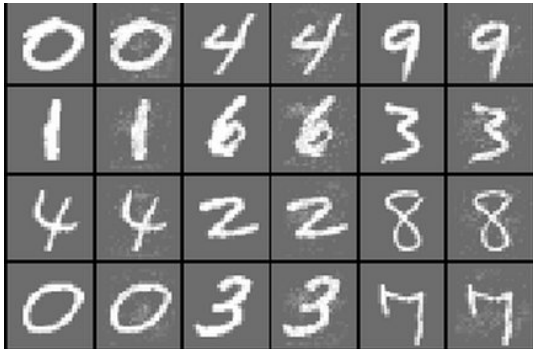
*"Intriguing properties of neural networks" joint work with Christian Szegedy, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus

How to?

- Negative examples generated with Backpropagation

- Constrained to be in feasible set (proper color range)

Cross model transfer



	Training Error
Model A	0%
Model B	0%

	Negative examples for Model A	Negative examples for Model B	Gaussian noise std = 0.1
Model A	100%	6.6%	0%
Model B	20.3%	100%	0%

Different fully connected networks trained on MNIST dataset. Average distortions by ~6%.

Cross training data transfer

	Training P1	Training P2
Model A	0%	2.4%
Model B	2.5%	0%

	Test distortion for A	Test distortion for B
Model A	100%	6.25%
Model B	26.2%	100%

Different fully connected networks trained on MNIST dataset. Distortions by ~6%.

Flaws - conclusions

- Different networks share properties, which are dependent on statistics of training sets (not only particular samples).

- Can negative examples be used to improve generalization ?

Q&A

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I am happy to take any questions.