

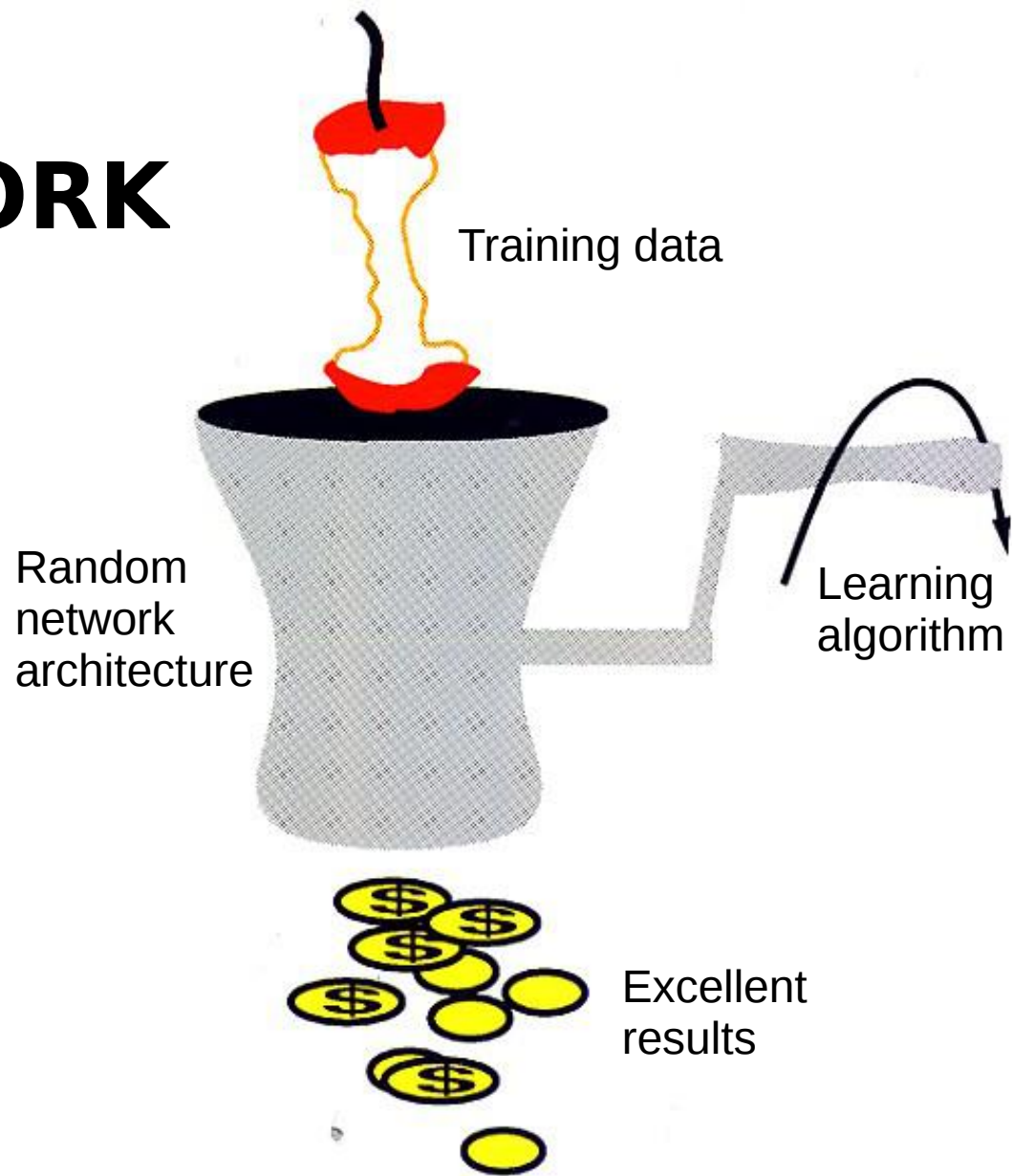
DEEP LEARNING - A PERSONAL PERSPECTIVE

Urs Muller

MIT 6.S191 Introduction To Deep Learning



NEURAL NETWORK MAGIC



THE REAL MAGIC OF DEEP LEARNING

Let's us solve problems we
don't know how to program



NEURAL NETWORKS RESEARCH AT BELL LABS, HOLMDEL 1985 - 1995

BELL LABS BUILDING IN HOLMDEL

Now called Bell Works



Around 1990:

6,000 employees in Holmdel

~300 in Research

~30 in machine learning, including:

Larry Jackel, Yann LeCun, Leon Bottou, John Denker, Vladimir Vapnik, Yoshua Bengio, Hans Peter Graf, Patrice Simard, Corinna Cortes, and many others

ORIGINAL DATABASE ~300 DIGITS

A handwritten document showing a list of names and their corresponding sequences of digits. The names are listed on the left, and the digit sequences are on the right. Some names have arrows pointing to specific digits in their sequences. The names include: Wagne, Hans, Paul, S. Field, Micah, Don, Carl, Albert, Kofi, Steve, Bob, Sam, Kwing, Larry, Greg, PDV, Ben, ether, and Todd H.

Name	Digit Sequence
Wagne	1 2 3 4 5 6 7 8 9 0
Hans	1 2 3 4 5 6 7 8 9 0
Paul	1 2 3 4 5 6 7 8 9 0
S. Field	1 2 3 4 5 6 7 8 9 0
Micah	1 2 3 4 5 6 7 8 9 0
Don	1 2 3 4 5 6 7 8 9 0
Carl	1 2 3 4 5 6 7 8 9 0
Albert	1 2 3 4 5 6 7 8 9 0
Kofi	1 2 3 4 5 6 7 8 9 0
Steve	1 2 3 4 5 6 7 8 9 0
Bob	1 2 3 4 5 6 7 8 9 0
Sam	1 2 3 4 5 6 7 8 9 0
Kwing	1 2 3 4 5 6 7 8 9 0
Larry	1 2 3 4 5 6 7 8 9 0
Greg	1 2 3 4 5 6 7 8 9 0
PDV	1 2 3 4 5 6 7 8 9 0
Ben	1 2 3 4 5 6 7 8 9 0
ether	1 2 3 4 5 6 7 8 9 0
Todd H.	1 2 3 4 5 6 7 8 9 0

Demonstrated need for large database for benchmarking

→ USPS database

→ MNIST database (60,000 digits)

USING PRIOR KNOWLEDGE

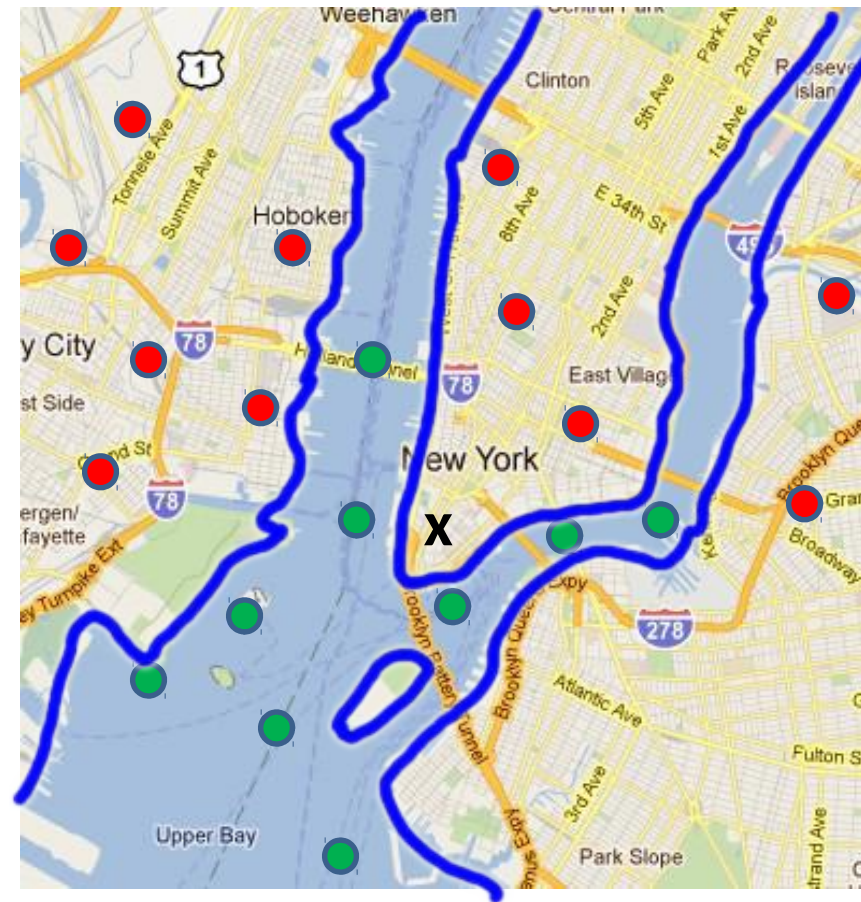
What class is point “X”?

If representation is north, south, east, west, then choose green

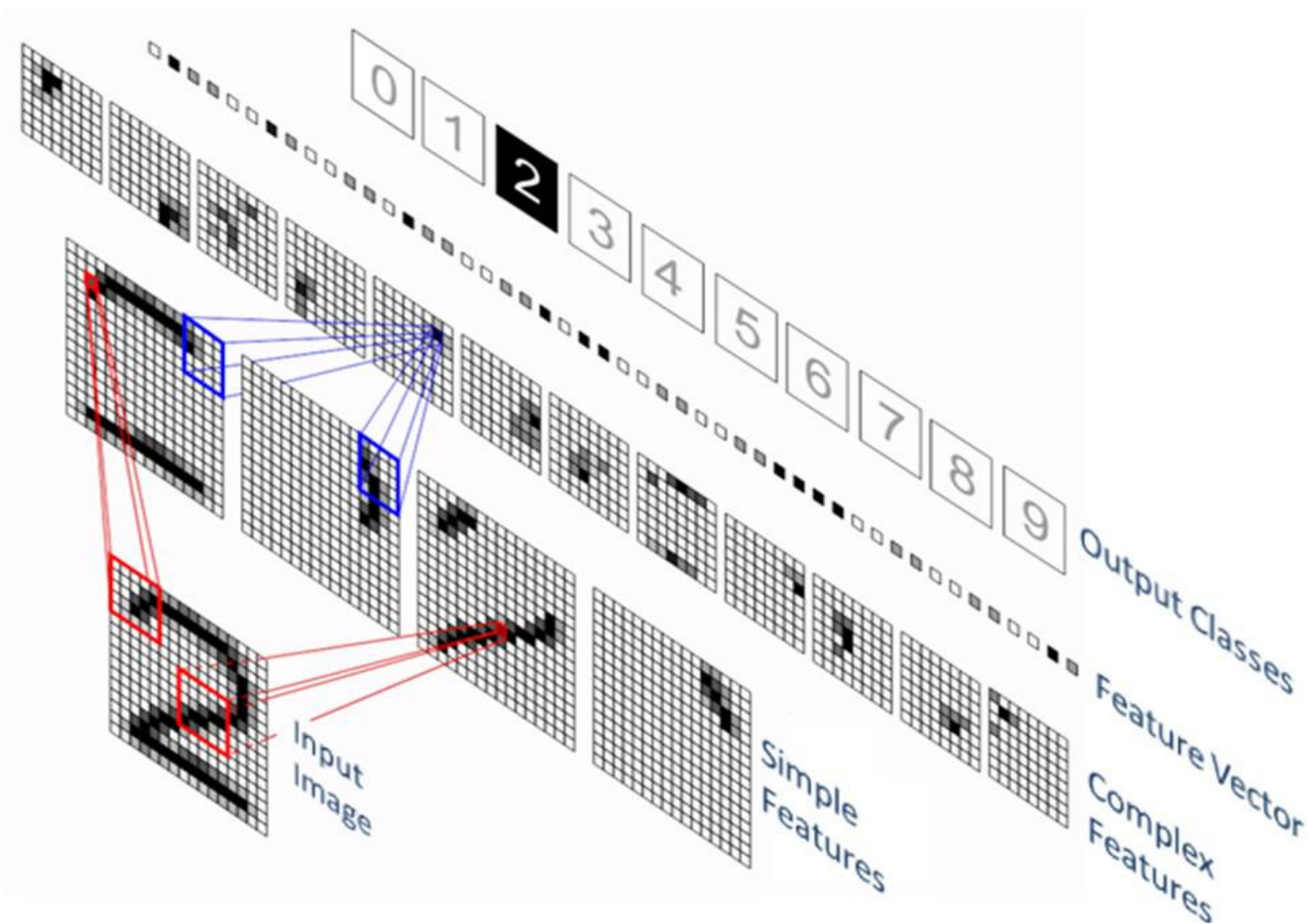
If better representation is elevation above sea level choose red

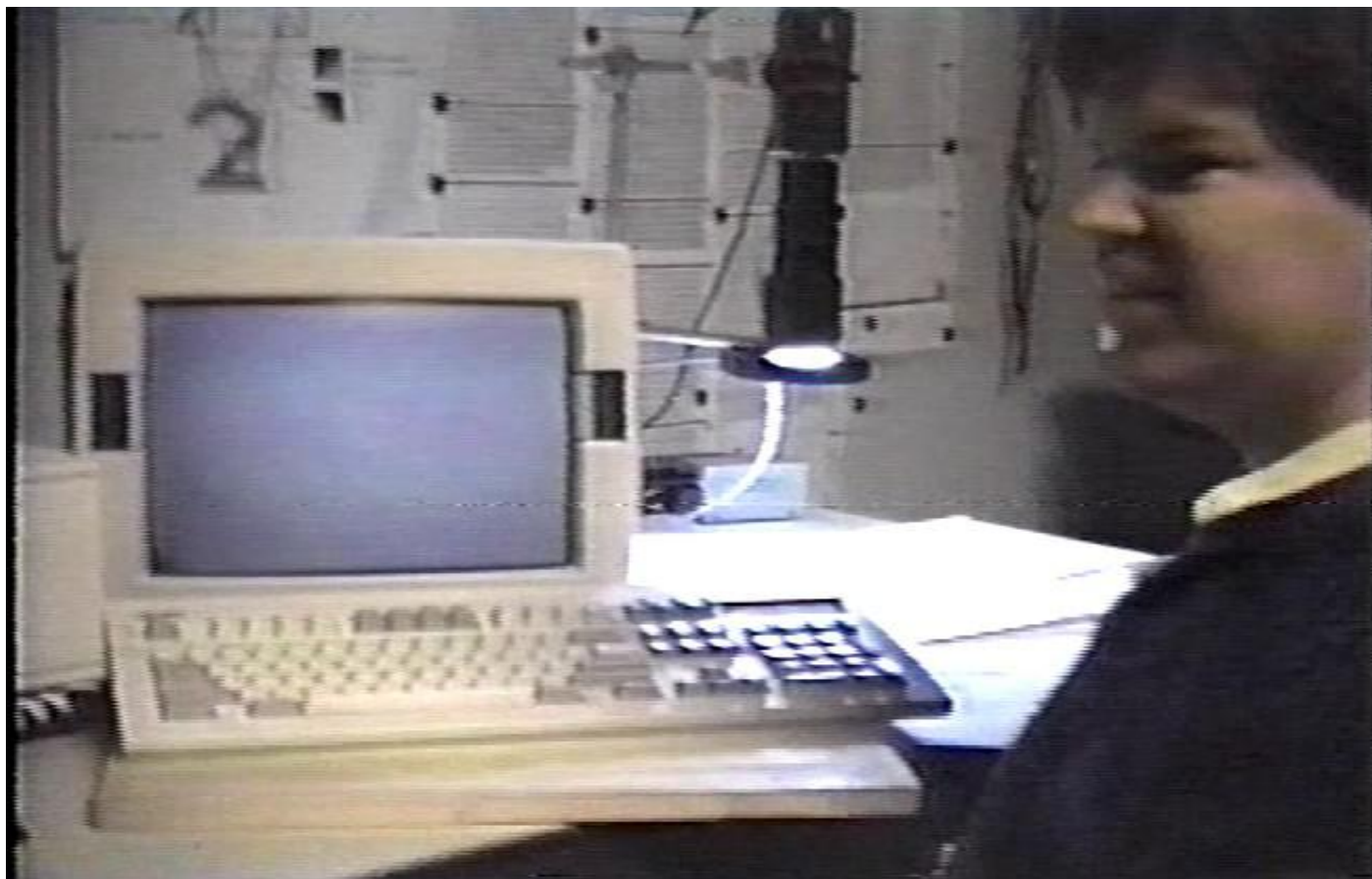
Using prior knowledge beats requiring tons of training data

Example: use convolutions for OCR



CONVOLUTIONAL NEURAL NETWORK (CNN)





LENET 1993

HOW WE CAME TO VIEW LEARNING

Largely Vladimir Vapnik's influence

Choose the right structure - "Structural Risk Minimization"

→ **Bring prior knowledge to the learning machine**

Capacity control - matching learning machine complexity to available data

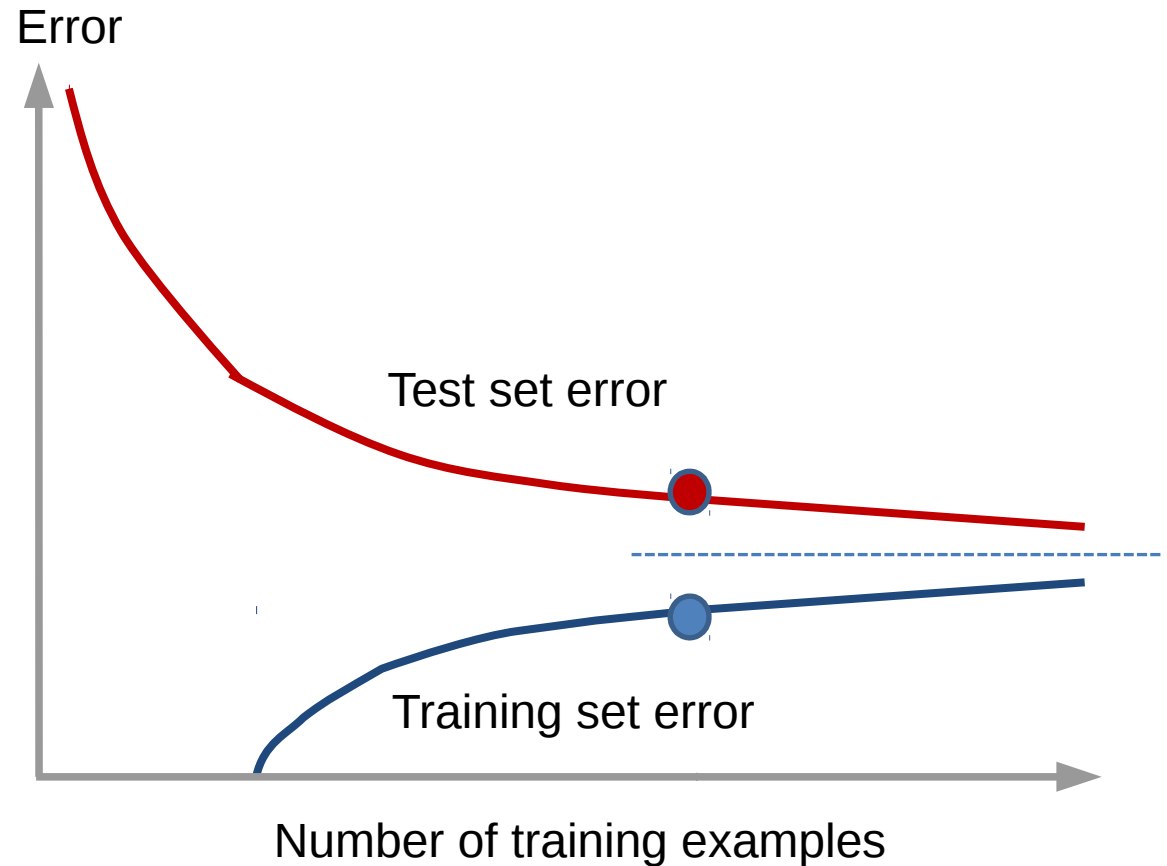
→ **Examine learning curves**

LEARNING CURVES

If test error \gg training error:
get more training examples or
decrease capacity

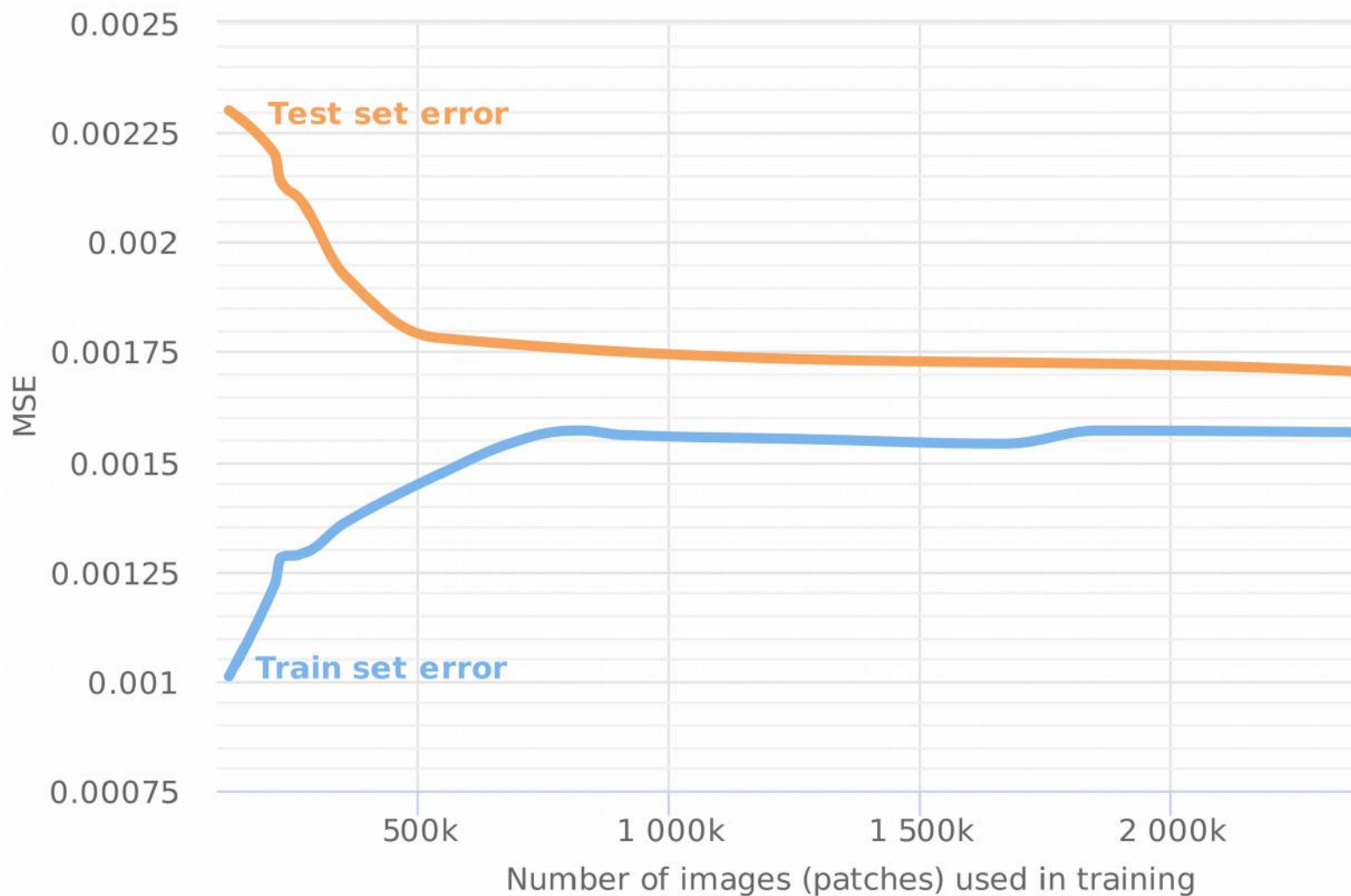
If test error \sim training error:
increase capacity

Smart structure allows low
errors with lower capacity



Cortes, Jackel, Wan-Ping Chiang: Limits on Learning Machine Accuracy Imposed by Data Quality
<http://papers.nips.cc/paper/918-limits-on-learning-machine-accuracy-imposed-by-data-quality.pdf>

PILOTNET LEARNING CURVE



THE (FRIENDLY) RECOGNIZER WAR

Who can read the digits best?

Comparison of Classifier Methods: A Case Study in Handwritten Digit Recognition

Léon Bottou*, Corinna Cortes, John S. Denker, Harris Drucker, Isabelle Guyon, L. D. Jackel,
Yann LeCun, Urs A. Müller†, Eduard Säckinger, Patrice Simard, and Vladimir Vapnik

AT&T Bell Laboratories, Holmdel, NJ 07733

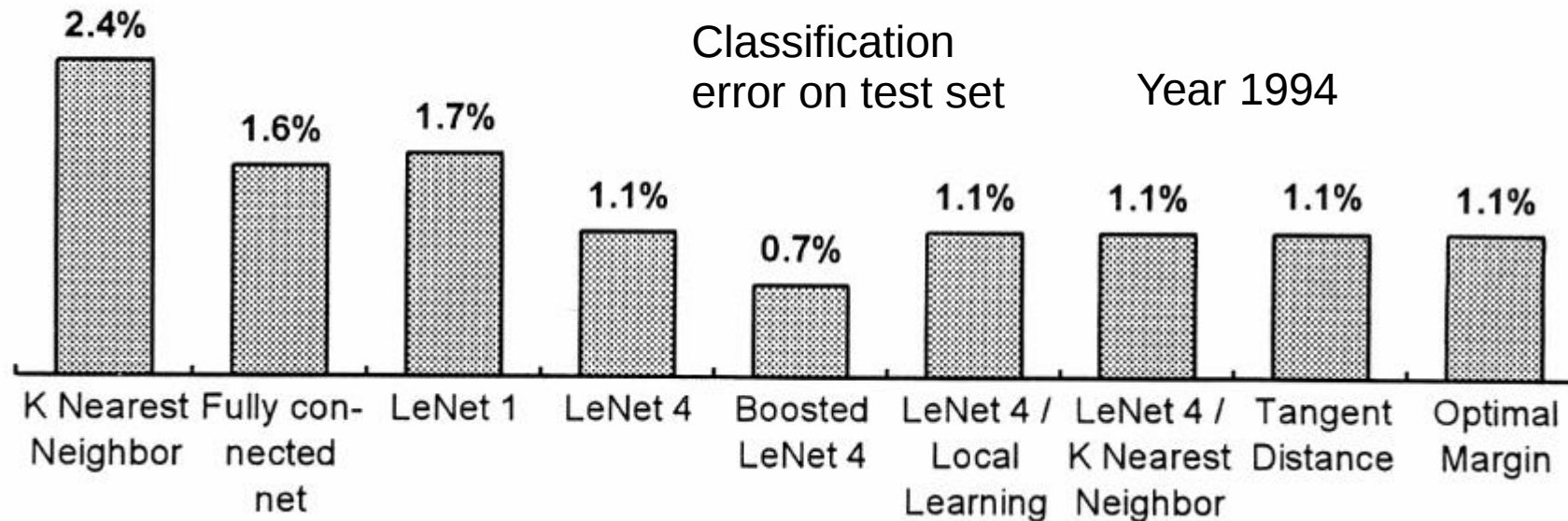
*Neuristique, 24 rue des Petites Ecuries, 75010 Paris, France

†Electronics Laboratory, Swiss Federal Institute of Technology,
ETH Zentrum, CH-8092 Zürich, Switzerland

Year 1994

<http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=576879>

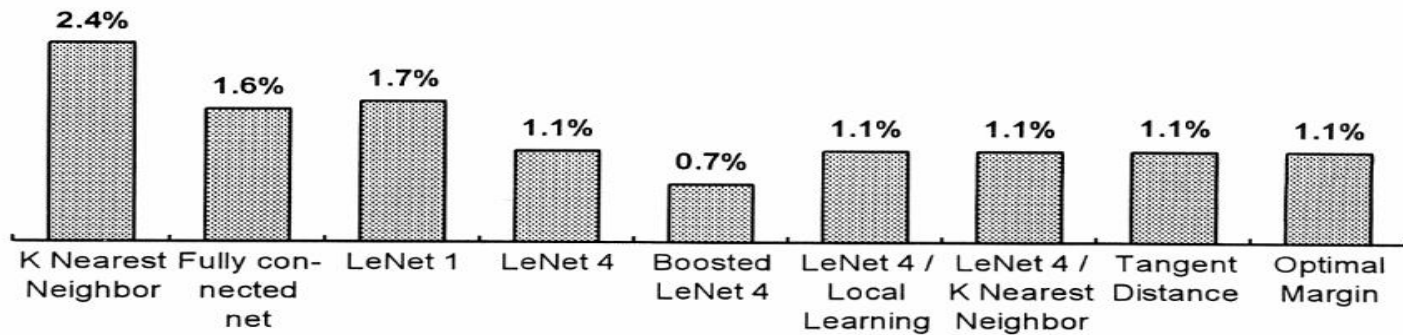
RESULTS ON MNIST DATA SET



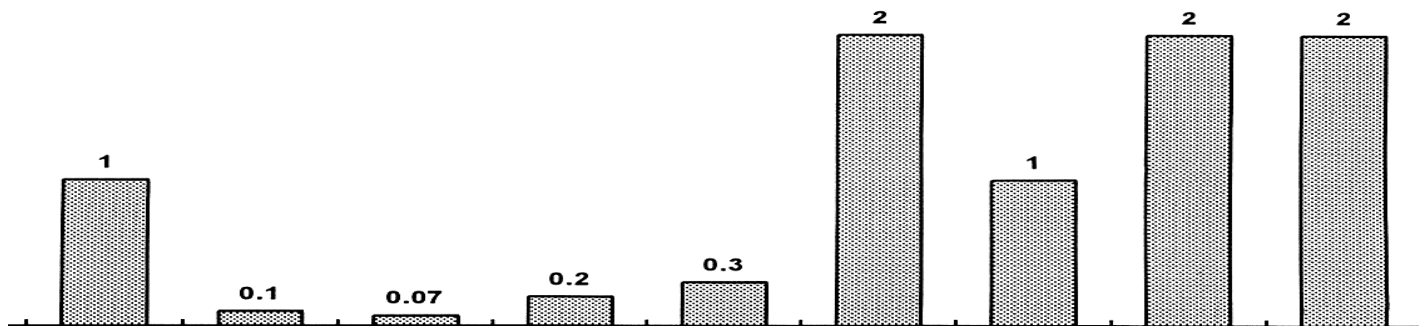
Larry Jackel: “In hindsight, the similar test errors are not so surprising since all the researchers were using variants of the same learning principles (everyone talked to Vladimir and studied the learning curves).”

The Optimal Margin (SVM) was remarkable because, unlike the other top performers, it did not include knowledge about the geometry of the problem.

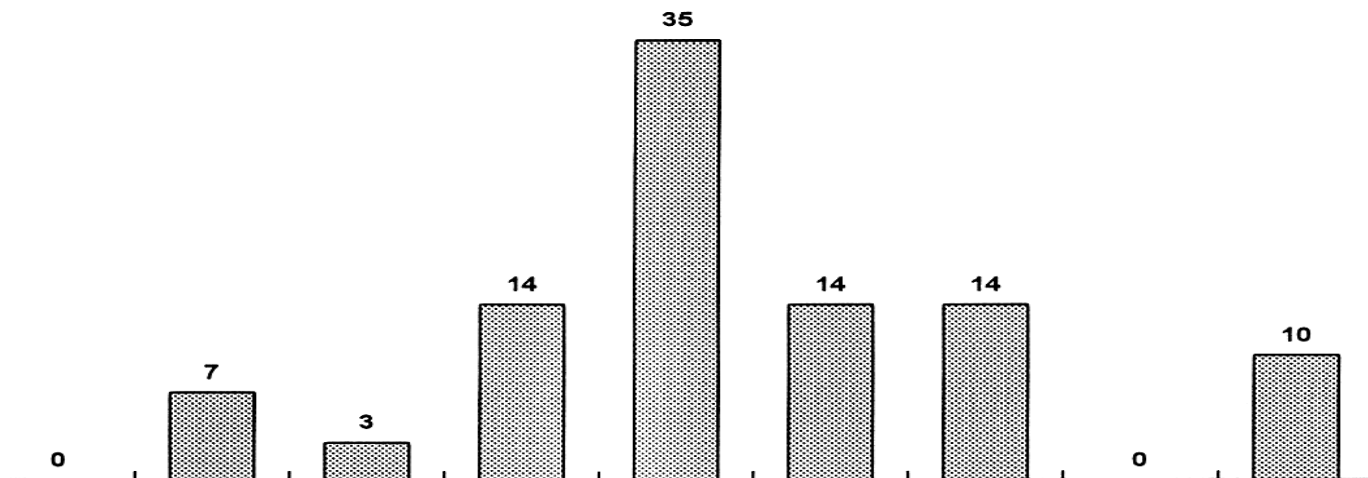
Classification error on test set



Inference time in sec on a Sparc 10



Training time in days on a Sparc 10



Year 1994

LESSONS LEARNED

Look at the data during all processing steps

Solid debugging tools are critical

Validate the training data

The work is experimental in nature

Work with real data

EPILOG

- 1995 Deployed Holmdel neural nets at Wachovia Bank – Eventually our technology was processing 20% of the checks written in the US
- 1995 AT&T Bell Labs fractured
- 2002 AT&T Labs – mass layoffs
- 2003 Bell Labs work led to new programs at DARPA – LAGR, Learning Locomotion, Deep Learning, Challenges
- 2012 Deep Learning becomes popular triggered by availability of data, compute power and ready commercial applications

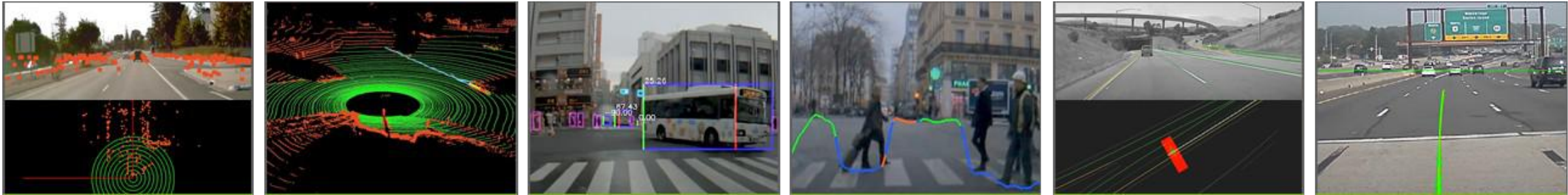


nVIDIA®

LEARNED AUTONOMY

DRIVE-AV

A full self-driving car stack



DRIVE AV

DRIVEWORKS SDK

DRIVE OS

DRIVE PX – AI CAR COMPUTER

NEW JERSEY TEAM GOAL

Solve the hard and unsolved autonomous vehicles (AV) problems using learning

To provide enhanced safety through algorithmic diversity

To create functionality that may not be achievable otherwise, such as perception-based turns or merges onto a busy highway

Additional AV labs in California, Boulder, Seattle, and Europe



**NVIDIA OFFICE AT BELL WORKS
IN HOLMDEL, NJ**

An ideal location for autonomous driving R&D

Private roads for easy testing

Quick access to diverse public roads

Space to store and work on the cars



CONVENIENT LOCATION

Close to New York City
(45 miles)

Accessible by commuter
train, ferry, bus, and car

Family friendly, yet near
a major metropolitan
area

Close to popular beaches
along the Jersey Shore



WHERE DO RULES FAIL?

Hand crafted features and rules work well when the problem domain is well understood

Simple rules, such as “follow the lane lines” fail quickly

→ Can you list every feature you look at while driving?

It is extremely hard to write down every single rule required for safe driving – it is relatively easy to collect lots of training data (just drive)

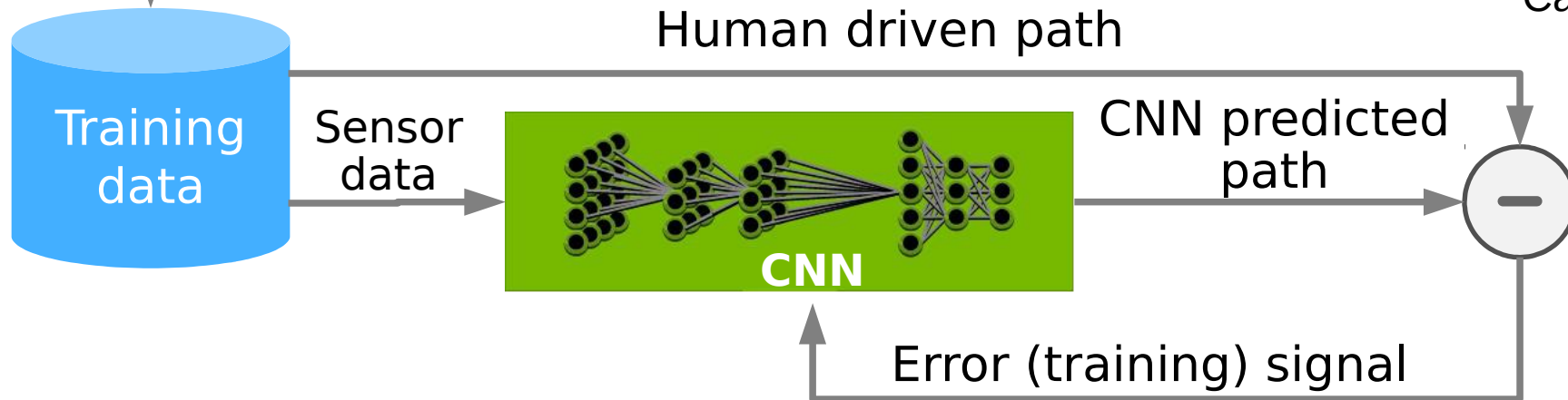
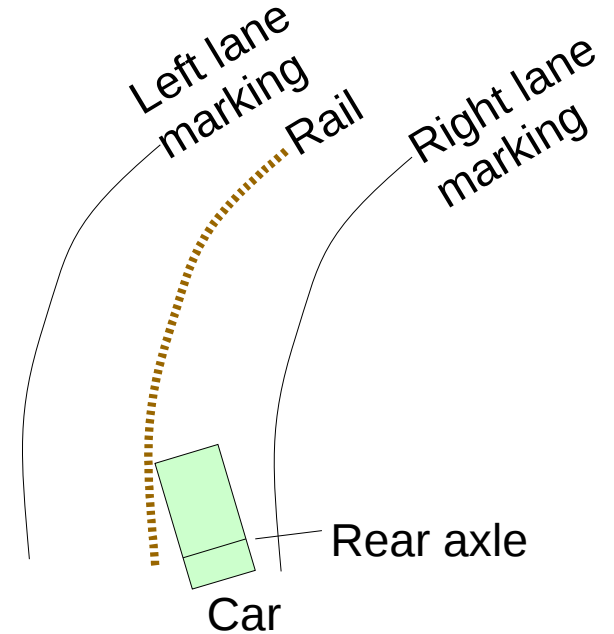


LEARNING TO PREDICT THE PATH



Record data from lots of humans driving their cars:

- Sensor data
- Human driven path



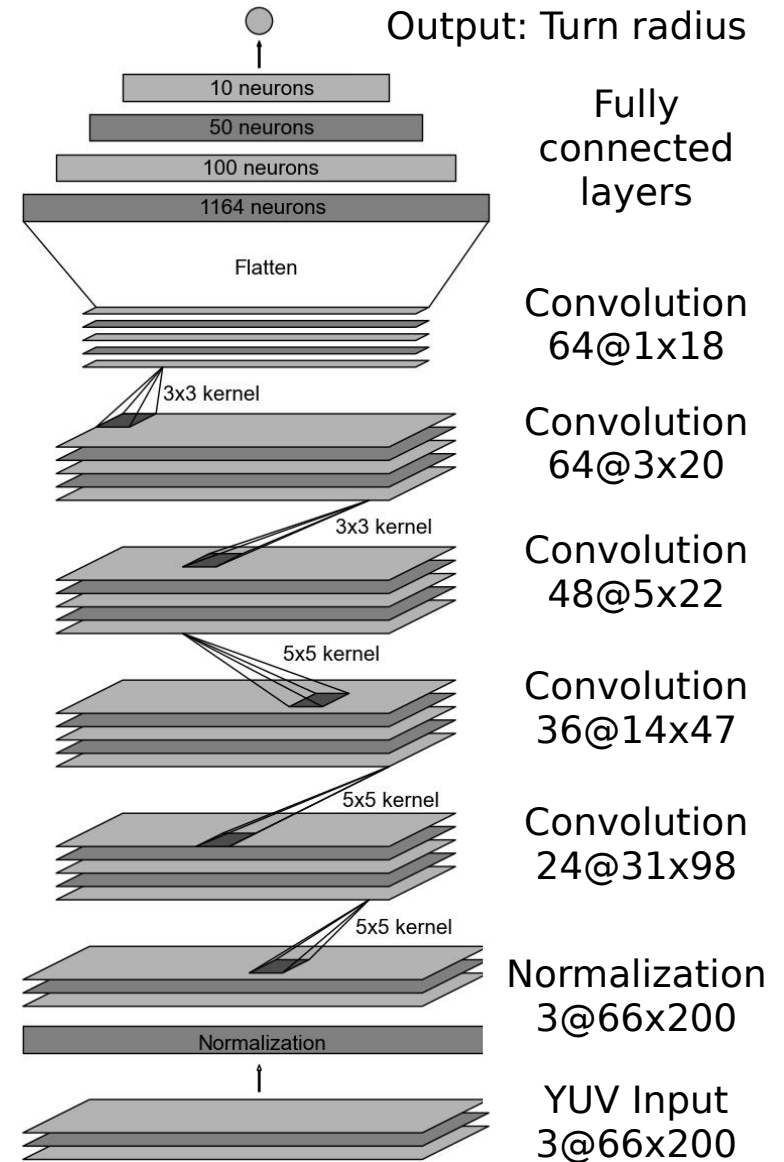
EXAMPLE ARCHITECTURE

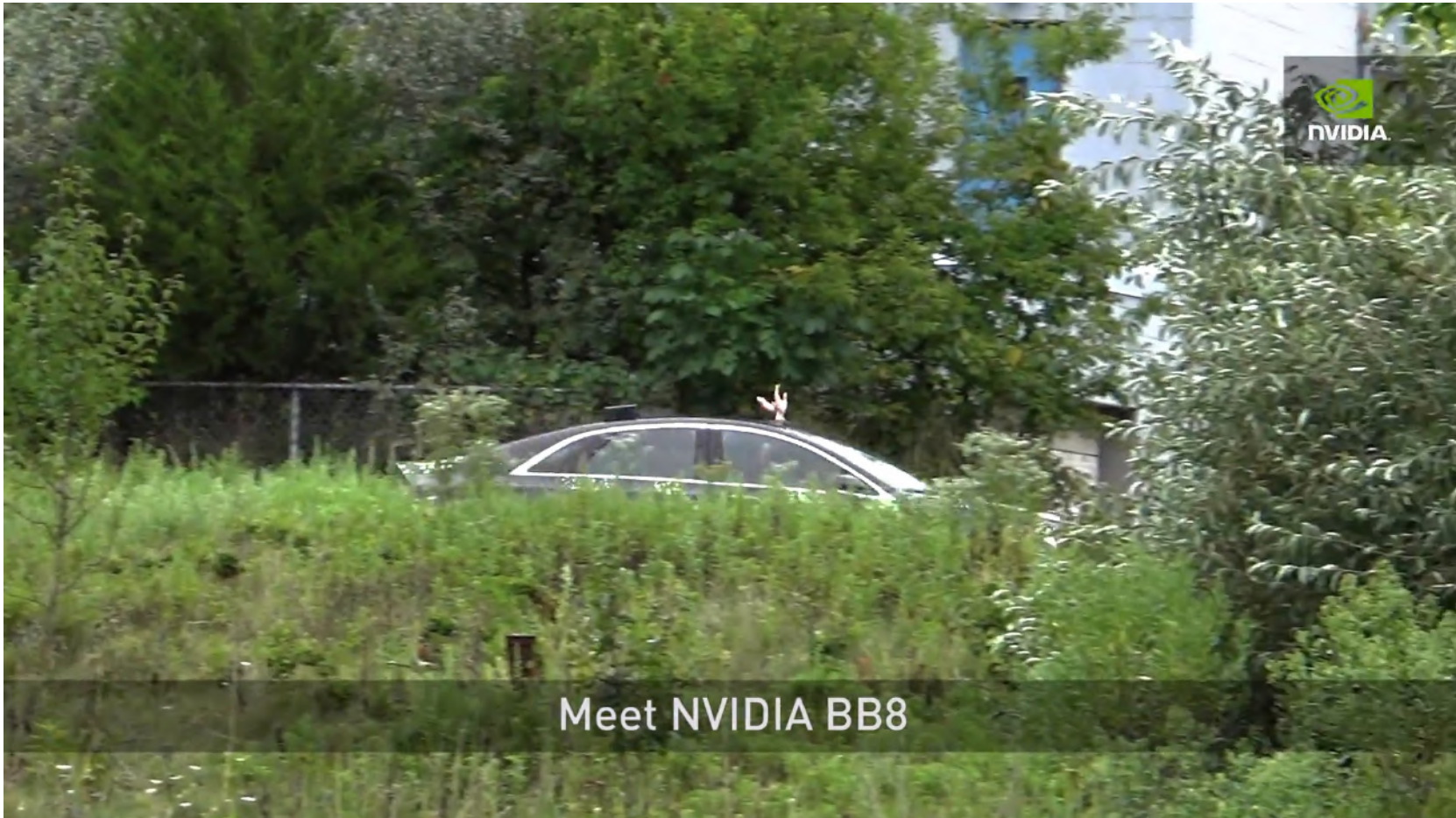
Single frame input with 200x66 pixel resolution

Input is from a single camera with a small patch cropped and scaled from the full image

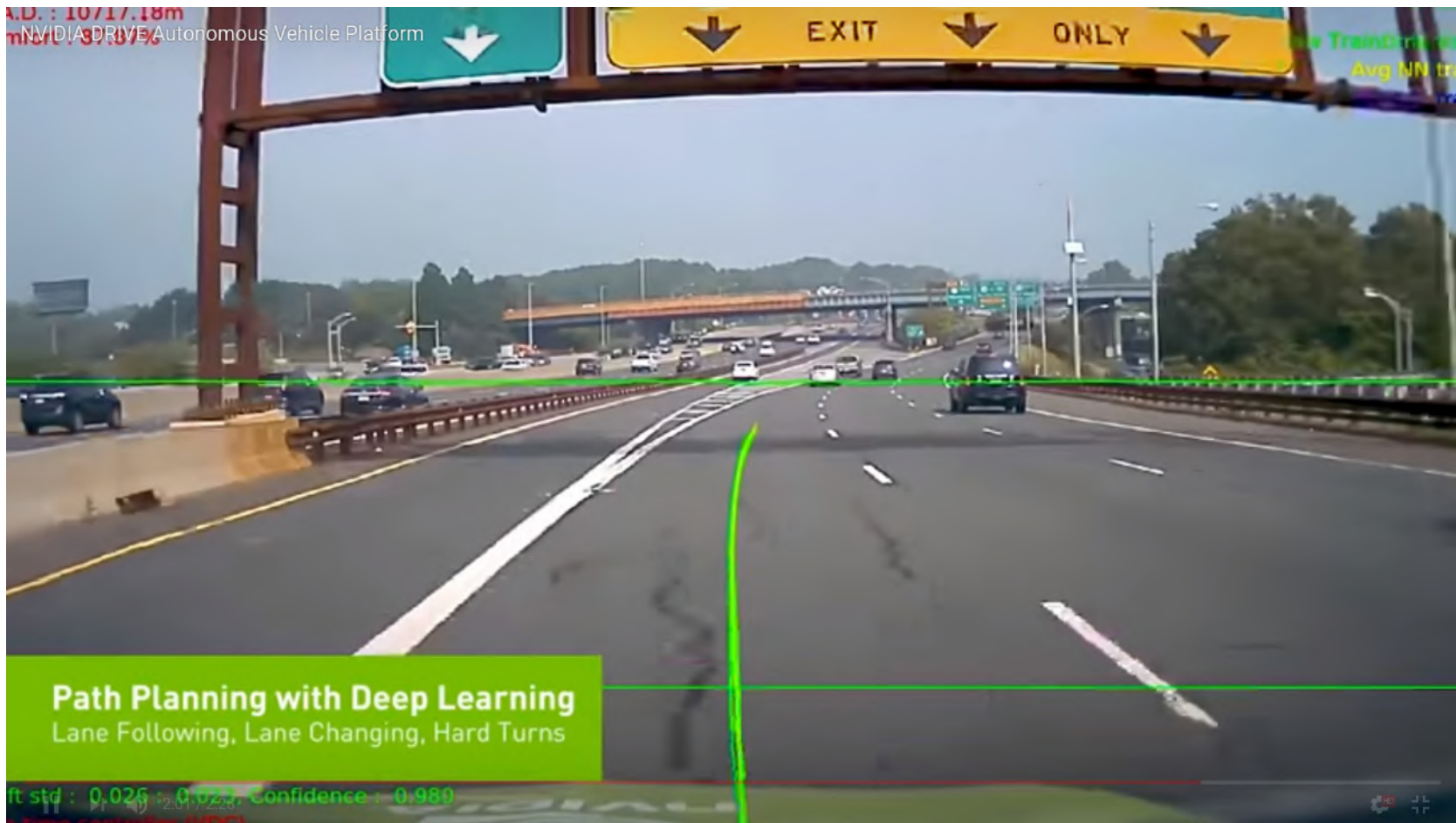
~250,000 neuron weights, not a huge network

The network grows as we use more sensors and handle harder tasks

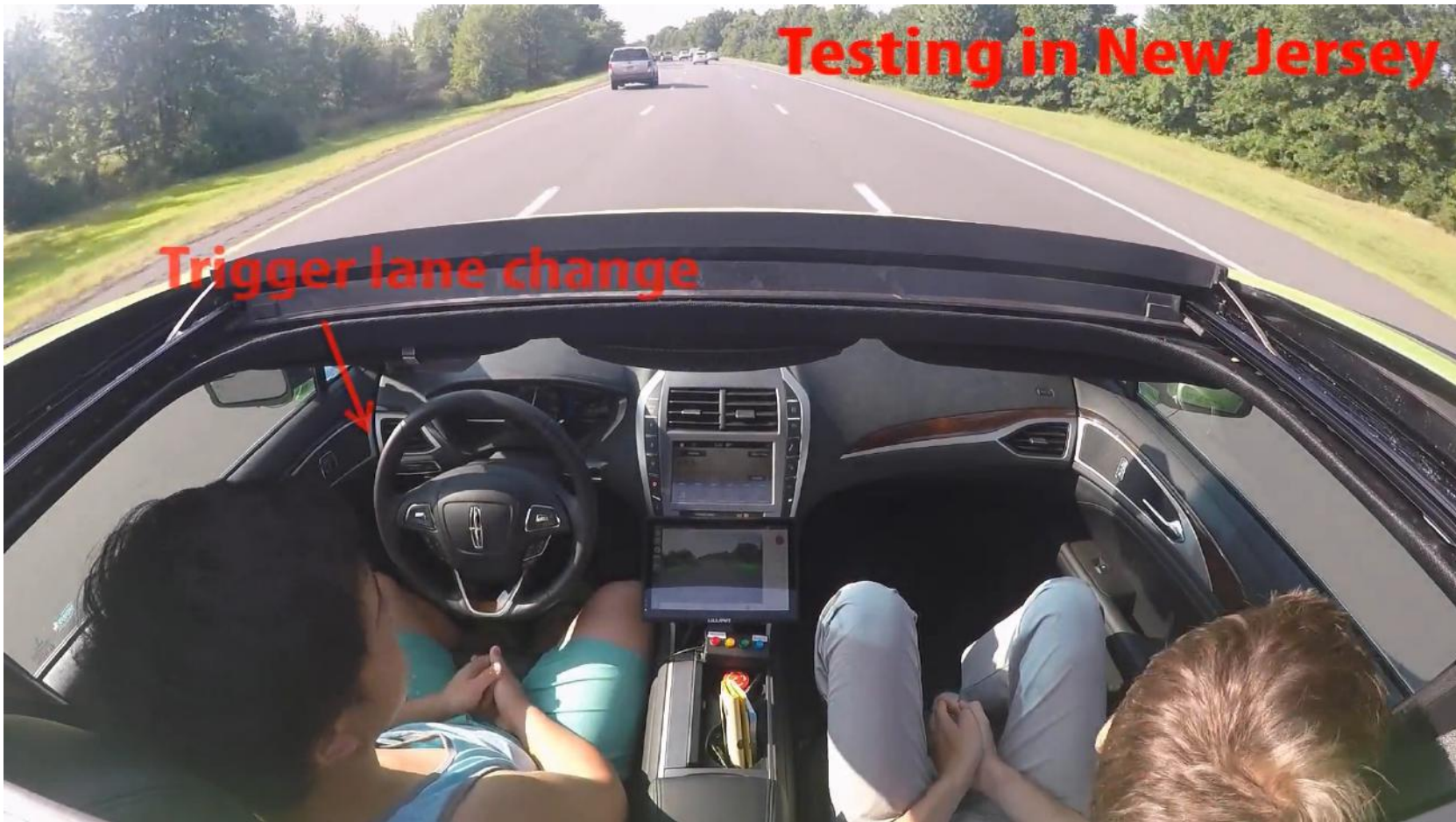




<https://www.youtube.com/watch?v=-96BEoXJMs0&t=39s>



DRIVING WITH LEARNED PATH PREDICTION



LEARNED LANE CHANGES



LEARNED TURNS

<https://www.youtube.com/watch?v=Sm-NBdSzP6E>



VISUALIZATION

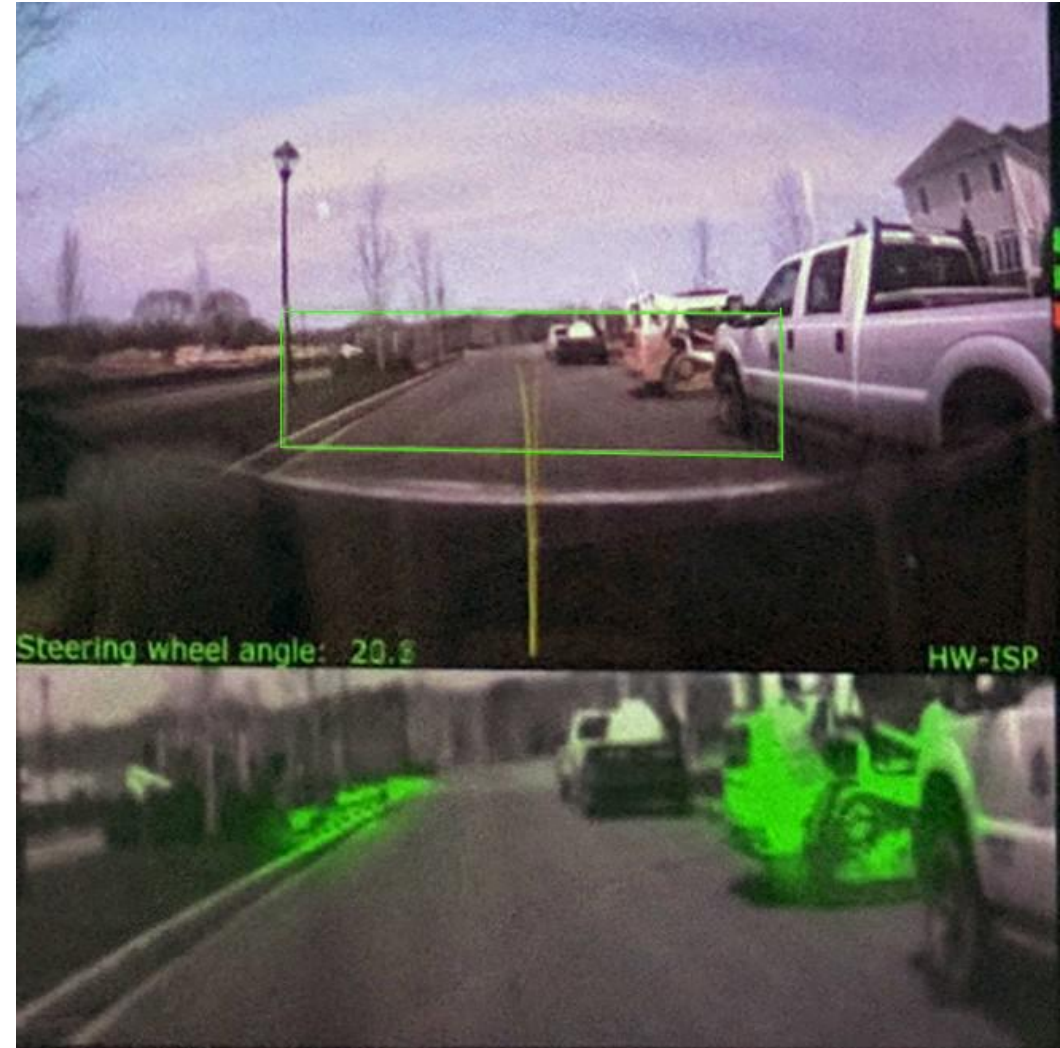
Where does the network look?

Visualization

Where does the network look?

VISUALIZATION

ATYPICAL VEHICLE CLASS



OPEN CHALLENGES

Deal with ambiguous situations

There is often more than one correct answer

Learn from imperfect behavior

Several observations in the same situation, most are correct, some are not correct



DRIVING IN THE SNOW

Thank You

