

Figure 1: The Transformer - model architecture.

# Deep Learning for NLP Workshop

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# Deep Learning for NLP Workshop

- Deep Learning Intro
- Introduction to NLP
  - spaCy
- Word Representations & Embeddings
  - Gensim Word vectors
- Deep Learning for NLP
  - PyTorch
  - MLP, CNN, RNN/LSTM, Attention
  - Sequence learning
- Transfer Learning and Advanced Models
  - Transformer Model
  - Self-supervised pre-training, ELMo, GPT, BERT, ...

<https://github.com/jayurbain/DeepNLPIntro2019>

# WORKSHOP PERSPECTIVE

- What this workshop is:
  - An intro to Natural Language Processing (NLP) using Deep Learning
  - Lectures followed by step-by-step hands-on exercises using Jupyter Notebooks
  - Emphasis is on the hands-on exercises
  - Executable from github repository on Google Colab
- This workshop is not:
  - Comprehensive review of NLP
  - Deep Learning from first principles
  - Extensive programming and knowledge of APIs

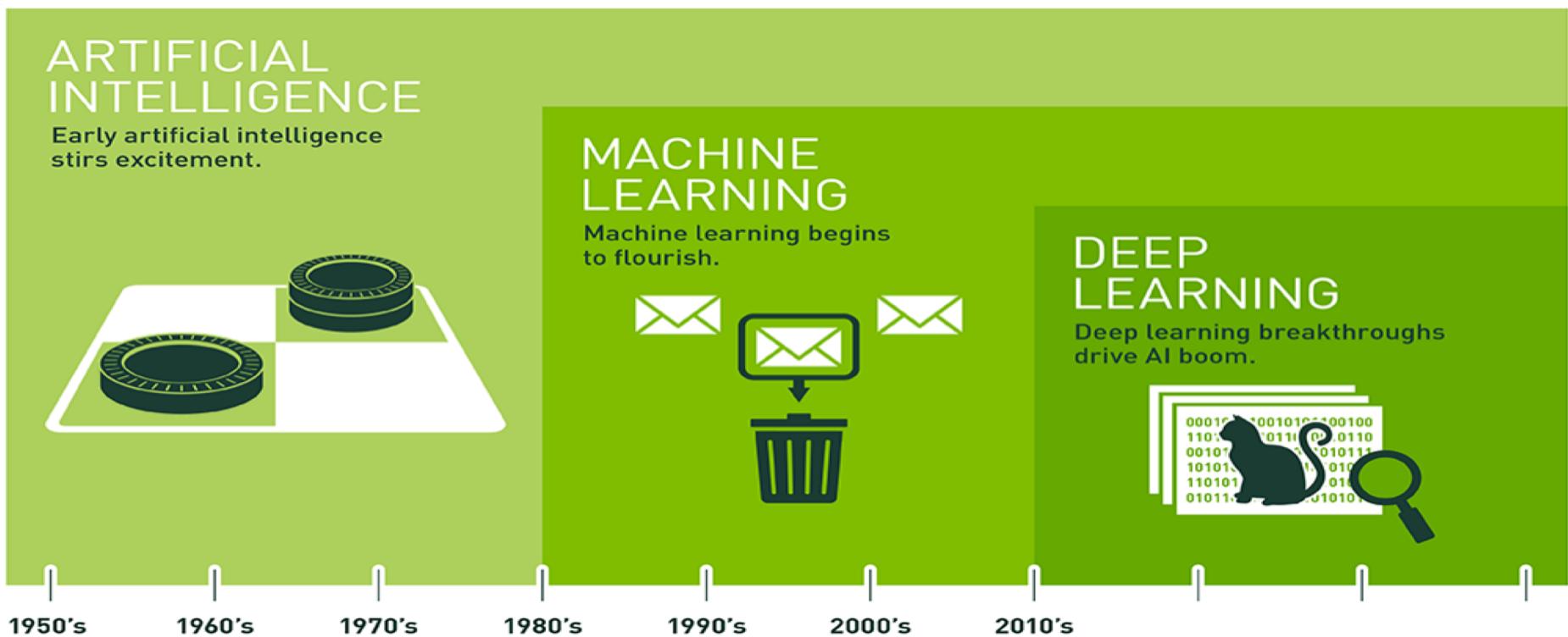
# EXPECTATIONS

- Assumptions:
  - Basic Python
  - Basic understanding of Machine Learning
- Nice to have:
  - Some deep learning, any NLP experience
- Consider working with a partner

## HOPEFULL TAKE AWAYS

- Ability to design a deep learning workflow to conduct NLP based text tasks
- Have a starting point for creating your own NLP projects

# ACCOMPLISHING COMPLEX GOALS

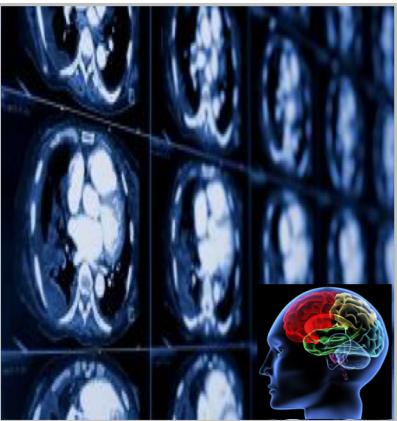


# Sweeping Across Industries

Internet Services



Medicine



Media & Entertainment



Security & Defense



Autonomous Machines



- Image/Video classification
- Speech recognition
- Natural language processing

- Cancer cell detection
- Diabetic grading
- Drug discovery

- Video captioning
- Content based search
- Real time translation

- Face recognition
- Video surveillance
- Cyber security

- Pedestrian detection
- Lane tracking
- Recognize traffic signs

# Deep learning = Learning representations/features

- The traditional model of pattern recognition (since the late 50's)

- Fixed/engineered features (or fixed kernel) + trainable classifier



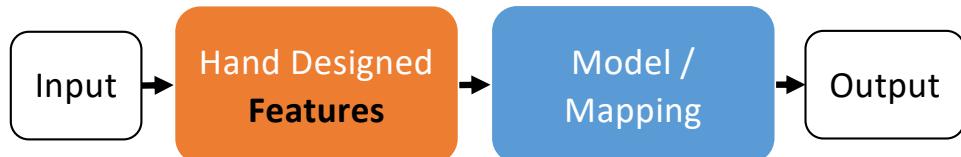
- End-to-end learning / Feature learning / Deep learning

- Trainable features (or kernel) + trainable classifier

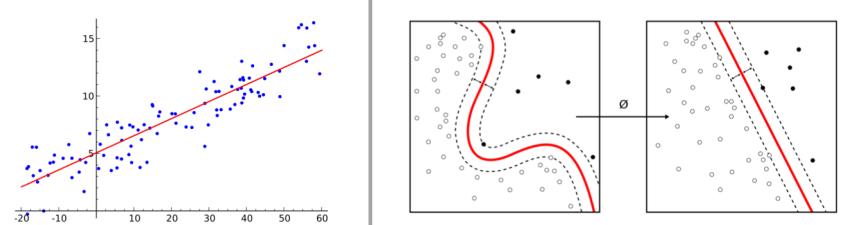


# Difference in Workflow

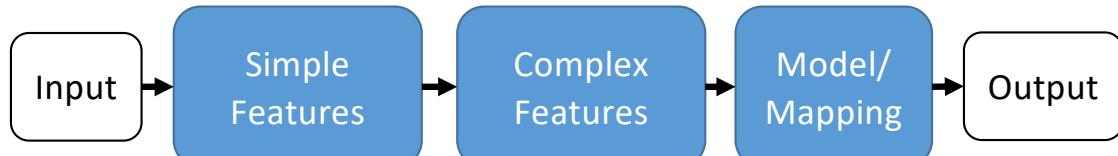
Classic Machine Learning [ 1990 : now ]



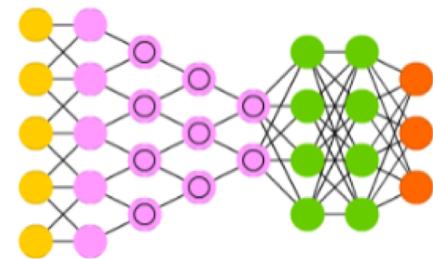
Examples [ Regression and SVMs ]



Deep/End-to-End Learning [ 2012 : now ]



Example [ Conv Net ]

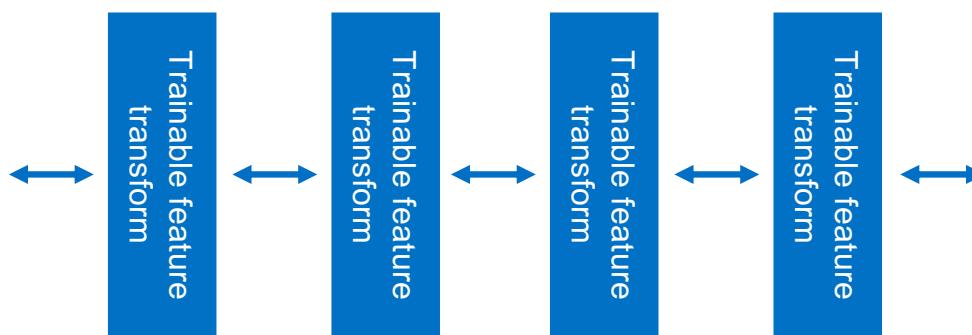


Machine learning workflow shifts from engineering features for “shallow” models to architecting deep learning models with the ability to learn hierarchical representations of features

# Trainable feature hierarchy

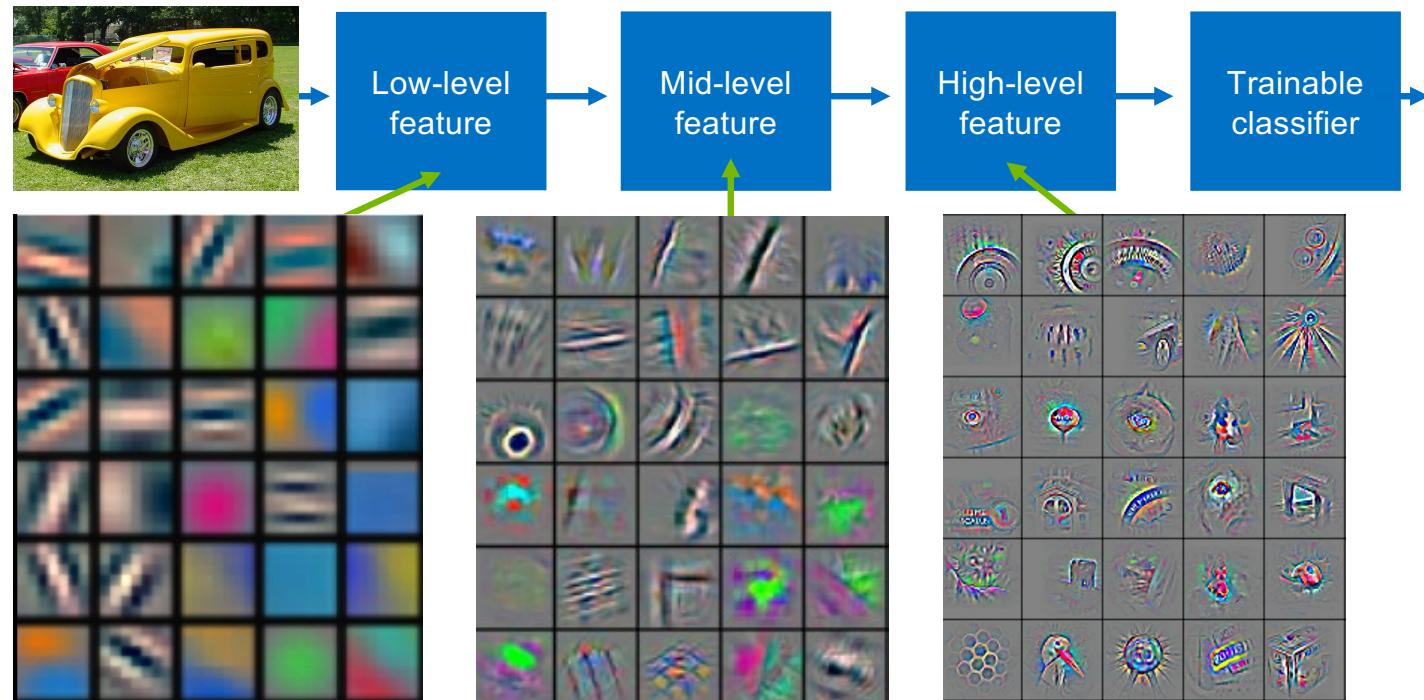
Hierarchy of representations with increasing level of abstraction. Each stage is a kind of trainable feature transform

- Image recognition
  - Pixel → edge → motif → part → object
- Text
  - Character → word → word group → clause → sentence → story/semantic understanding
- Speech
  - Sample → spectral band → sound → ... → phone → phoneme → word



# Deep learning = learning hierarchical representations

It's **deep** if it has **more than one stage** of non-linear feature transformation

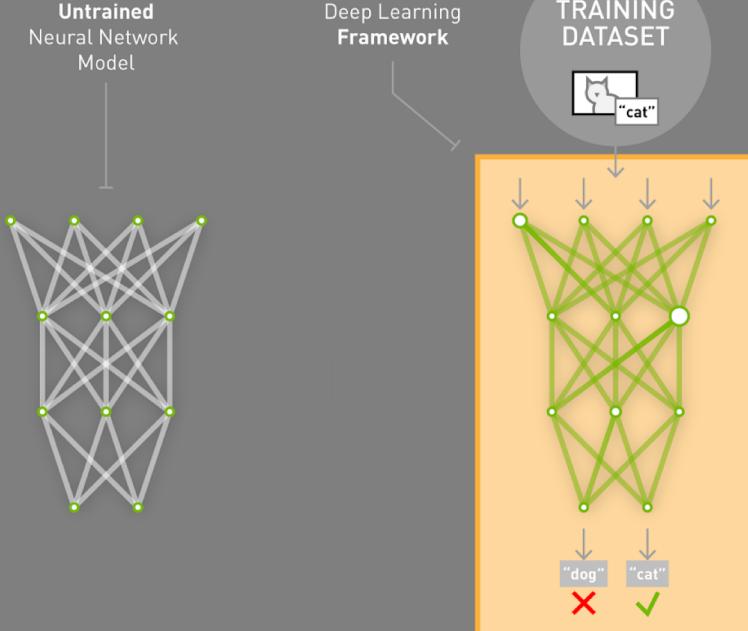


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

# DEEP LEARNING

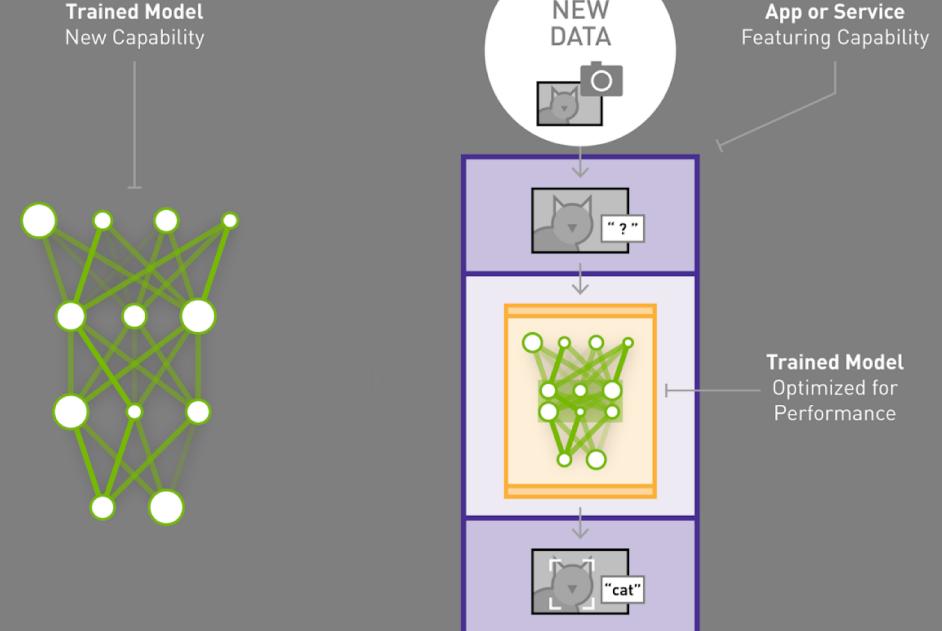
## TRAINING

Learning a new capability  
from existing data



## INFERENCE

Applying this capability  
to new data



# Rationale for Deep Learning

Costs of acquiring and storing large quantities of heterogeneous data have dropped significantly.

The ability to extract actionable knowledge from such datasets has become critical for companies to maintain a competitive advantage.

Significant improvements in deep learning algorithms enabled by GPU processing provide new application opportunities across industries.

Deep Learning has set new performance standards in many machine learning applications.