

LECTURE 1: INTRODUCTION

DEEP LEARNING FOR NATURAL LANGUAGE PROCESSING

Anatolii Stehnii

Software Developer in DataRobot

Yuri Guts

Software Developer in DataRobot

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Ukrainian Catholic University

APPLIED
SCIENCES
FACULTY ●

WHAT YOU ALREADY HAVE LEARNED

- ▶ What is Natural Language Processing
- ▶ NLP levels
- ▶ NLP applications
- ▶ What are main NLP problems

MYSTERY OF LANGUAGE

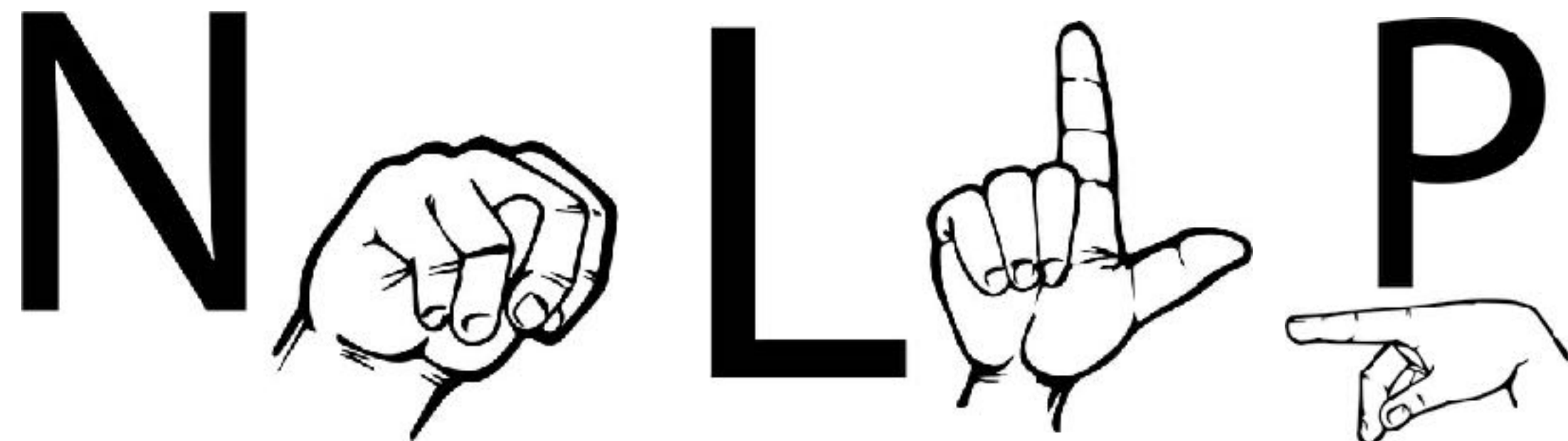
“... language is eccentric among animal communication systems ... It has a core combination of features—semanticity, discrete infinity, and decoupling—that is found nowhere else in nature to our present knowledge ...”

A Cognitive View of Language Evolution <https://www.frontiersin.org/articles/10.3389/fpsyg.2015.01434/full>

Noam Chomsky: Cartesian Linguistics https://en.wikipedia.org/wiki/Cartesian_linguistics

LANGUAGE PROPERTIES

- ▶ **Discrete/symbolic/categorical** symbols: guitar - 🎸 gun - 🔫.
- ▶ **Naturally** evolved and contains multiple latent relations.
- ▶ Can have multiple **material encodings**: sound, writings, gesture.
- ▶ **Hierarchy** of symbols with steadily increasing degree of symbols complexity: letters, words, sentences, paragraphs, etc. **Infinite** creative possibilities.

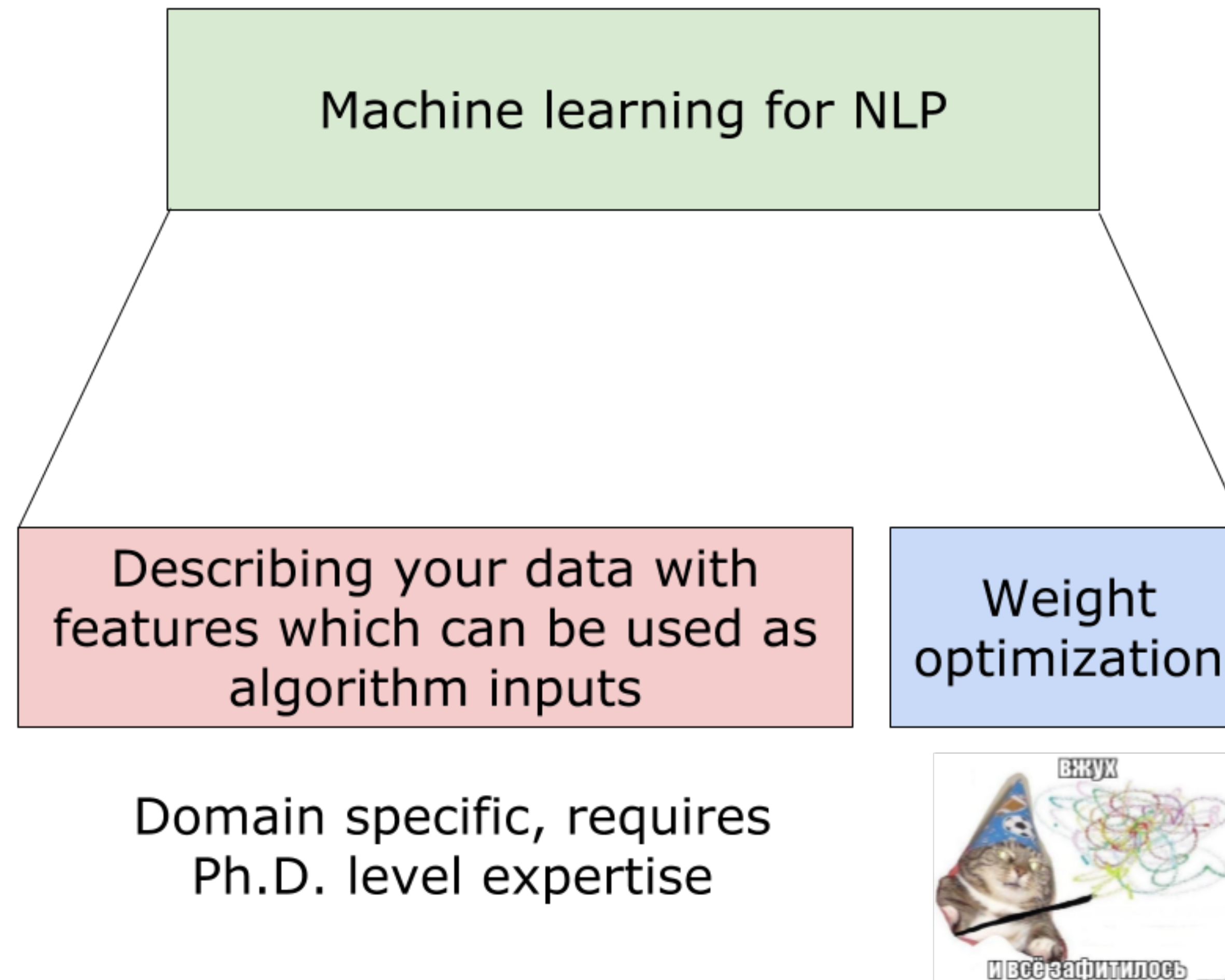


MACHINE LEARNING AND NATURAL LANGUAGE

Discrete structure of natural language and its large vocabulary leads to a **sparsity** of its numeric representation.

Also, straightforward **language encoding** (BoW, TF-IDF) ignores **syntactic** and **semantic** information stored in a sentence structure. Feature engineering heavily relies on **human-designed** representations and requires a **substantial expertise**.

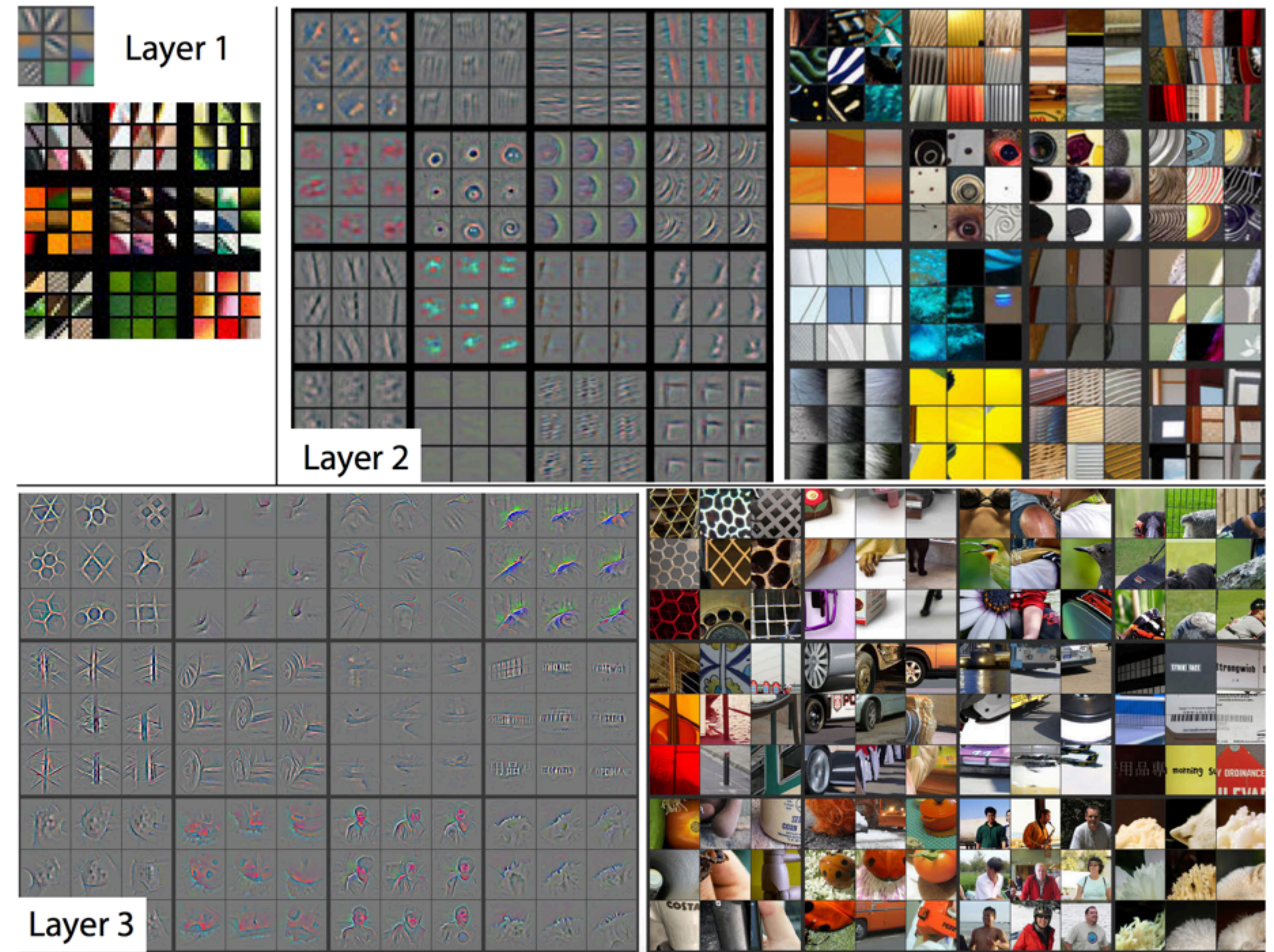
MACHINE LEARNING AND NATURAL LANGUAGE



DEEP LEARNING: REPRESENTATION LEARNING

Deep neural networks are composed from multiple **layers** (aka non-linear vector transformations), which are optimized by a supervision signal to provide domain specific hierarchical **representations (features)** of input data.

Deep learning can be used in NLP to avoid a process of complex manual feature engineering. **Syntactic** and **semantic** features can be incorporated by a NN from training data.



NOT INDEPENDENT INPUTS

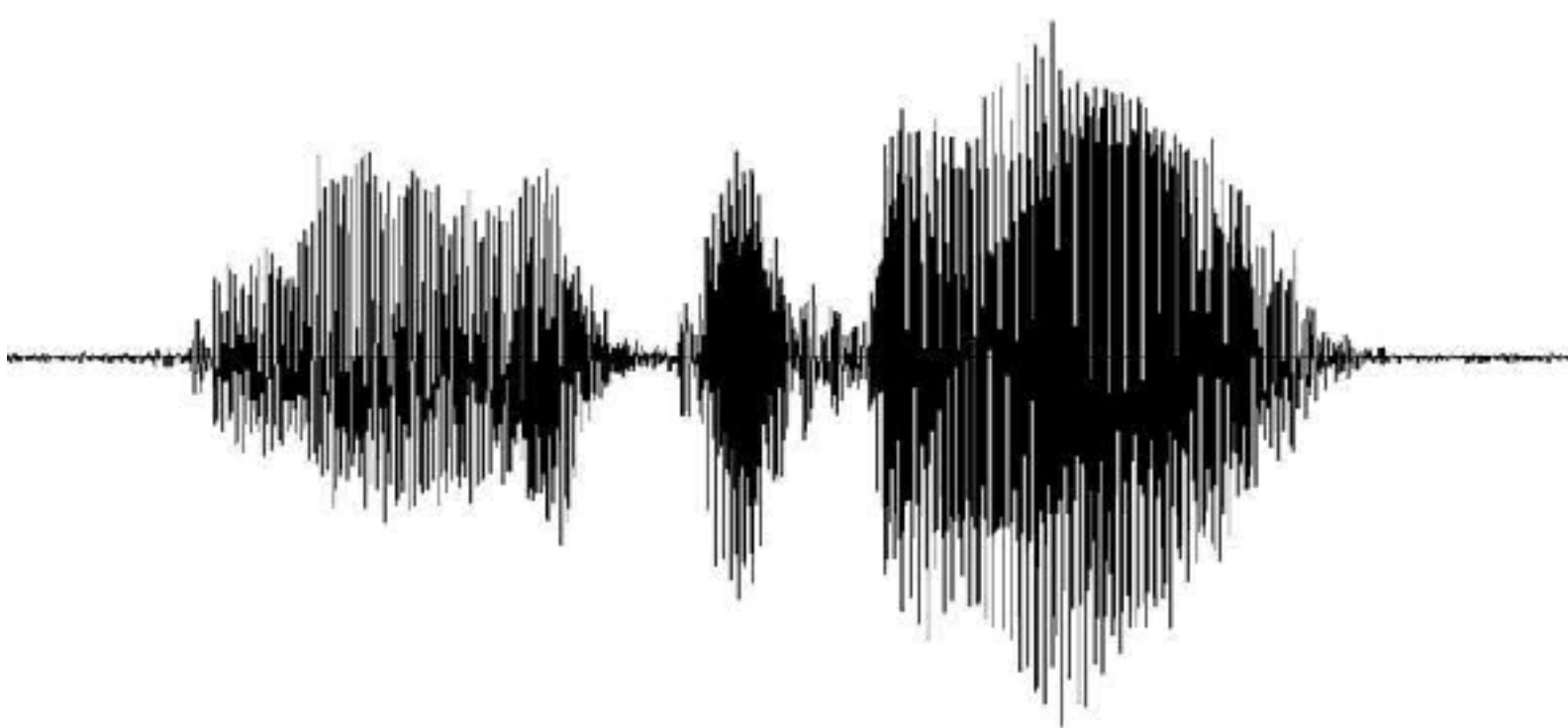
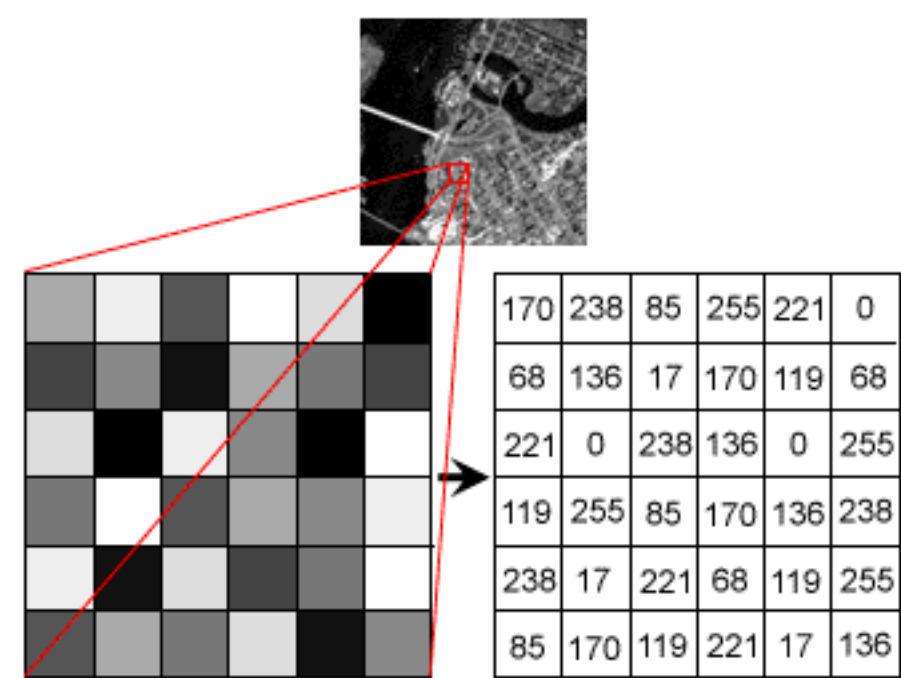
Classical machine learning algorithms, like logistic regression uses an statistical assumption, that their inputs are **independent random variables**.

Low-level features of natural language (words, characters) are not independent. **Probability** of each word depends on it's context.

$$P(word, prev.words) = P(word|prev.words) \cdot P(prev.words)$$
$$P(word) \neq P(word|prev.words)$$

Q: What other examples of not independent data do you know?

NOT INDEPENDENT INPUTS



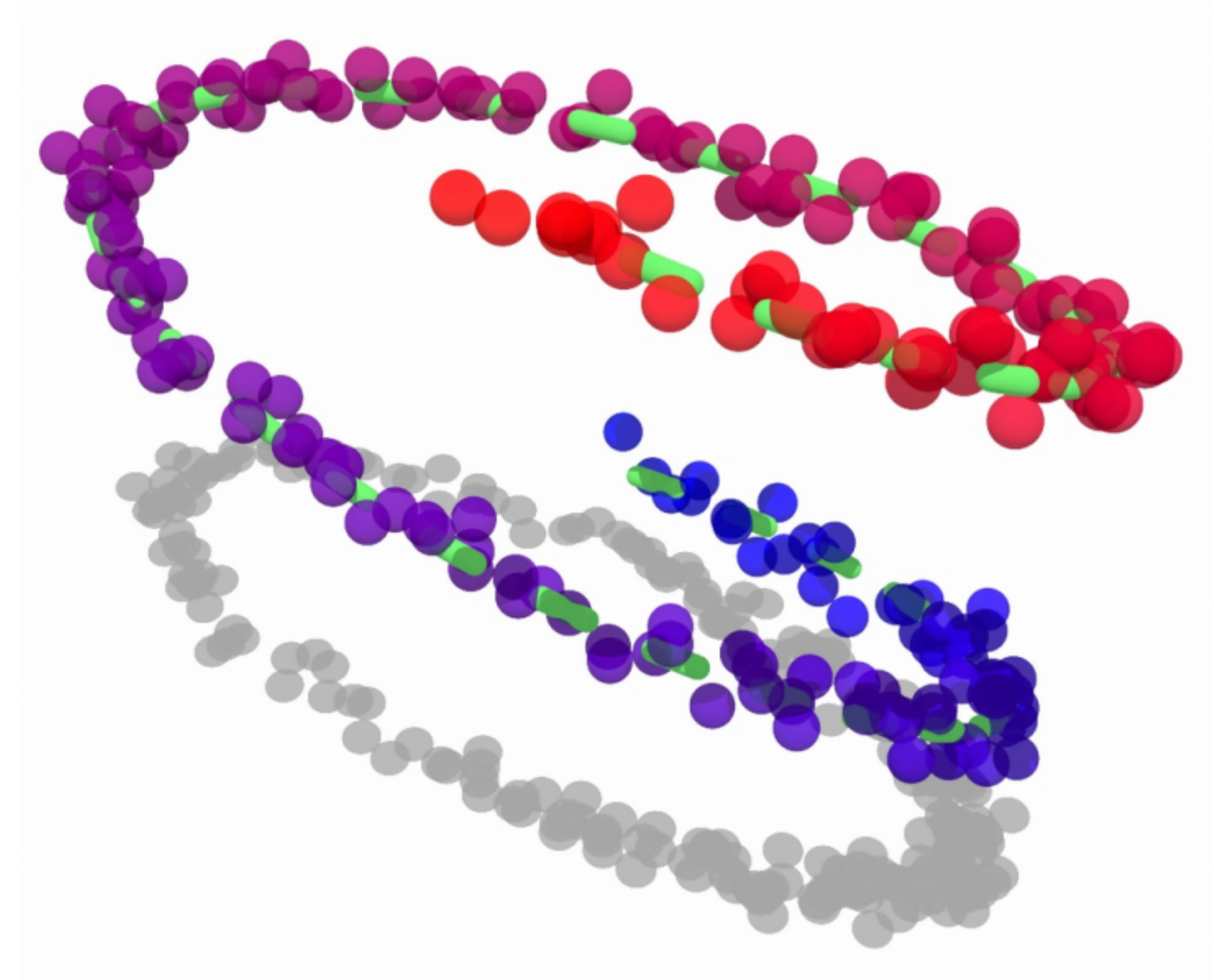
I see a brown bear.

I see a blue bird.

I see the red crab.

MANIFOLD HYPOTHESIS

Feature space of **cognitive information** (sound, image, text) are tremendously large (AlexNet input $227 \times 227 = 51529$ dimensions). However, only a tiny fraction of this space is used. Meaningful images are embedded in low-dimensional **manifolds**.



Zachary Pincus, 2010

DEEP LEARNING: MANIFOLD HYPOTHESIS

Deep learning techniques (like convolution or recurrent connection) assumes, that input data are **not distributed independently** over their feature space. During training, neural network **learns to unwrap** this manifolds and project data to a low-dimensional **representations**.

COURSE INFO

Teachers: Anatolii Stehnii, Yurii Guts.

Evaluation: practical assignments for each day.

Prerequisites: linear algebra, applied statistics, python (numpy).

Environment:

Python ≥ 3.5 , pytorch $\geq 0.4.0$, nltk, spacy, jupyter

COURSE STRUCTURE

Day 1

- ▶ Unsupervised deep learning for NLP
- ▶ Word embeddings

Day 2

- ▶ Convolution networks
- ▶ Recurrent networks
- ▶ Recursive networks

Day 3

- ▶ Sequence-to-sequence networks
- ▶ Attention and its friends
- ▶ Reinforcement learning for NLP