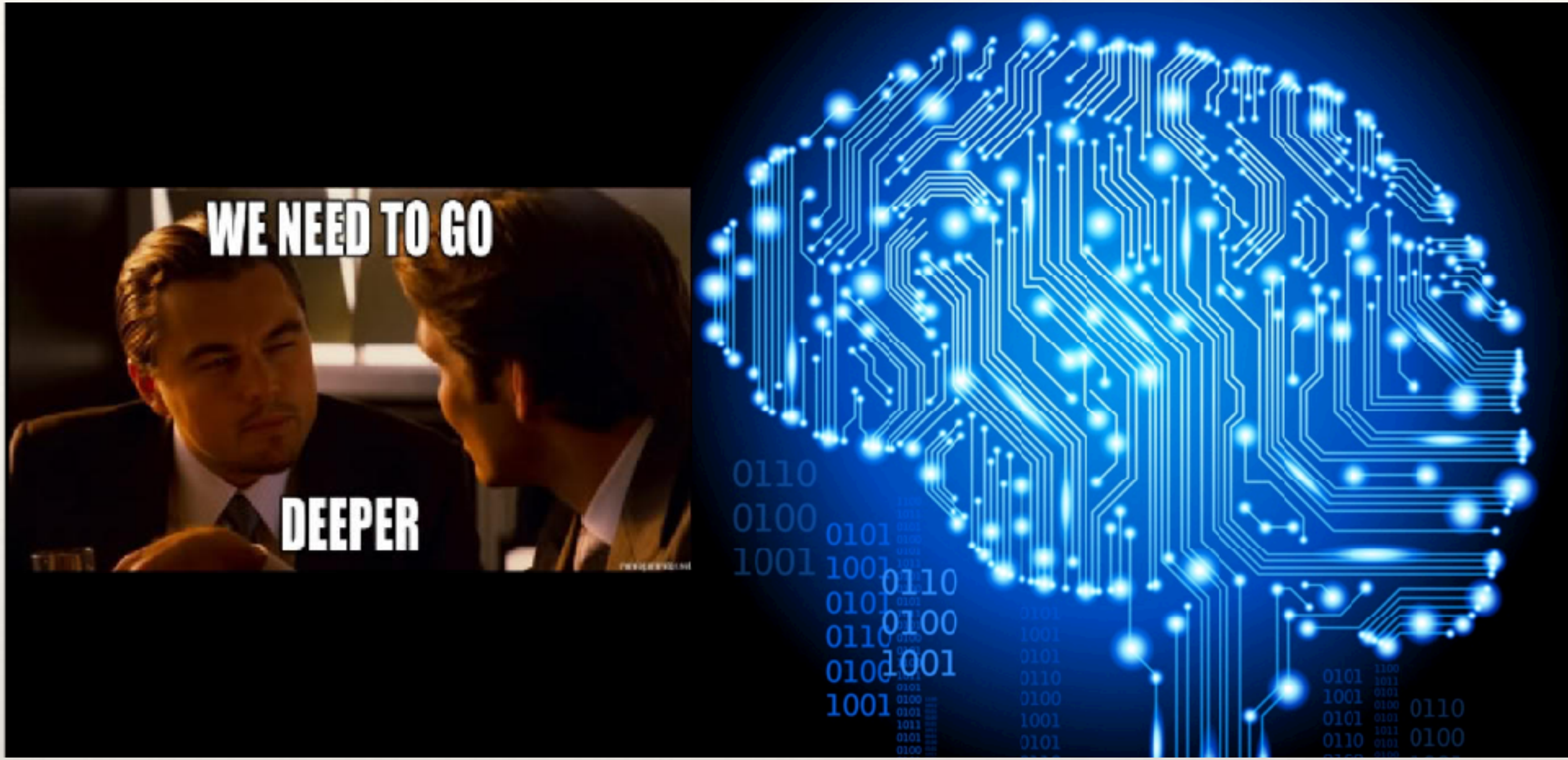


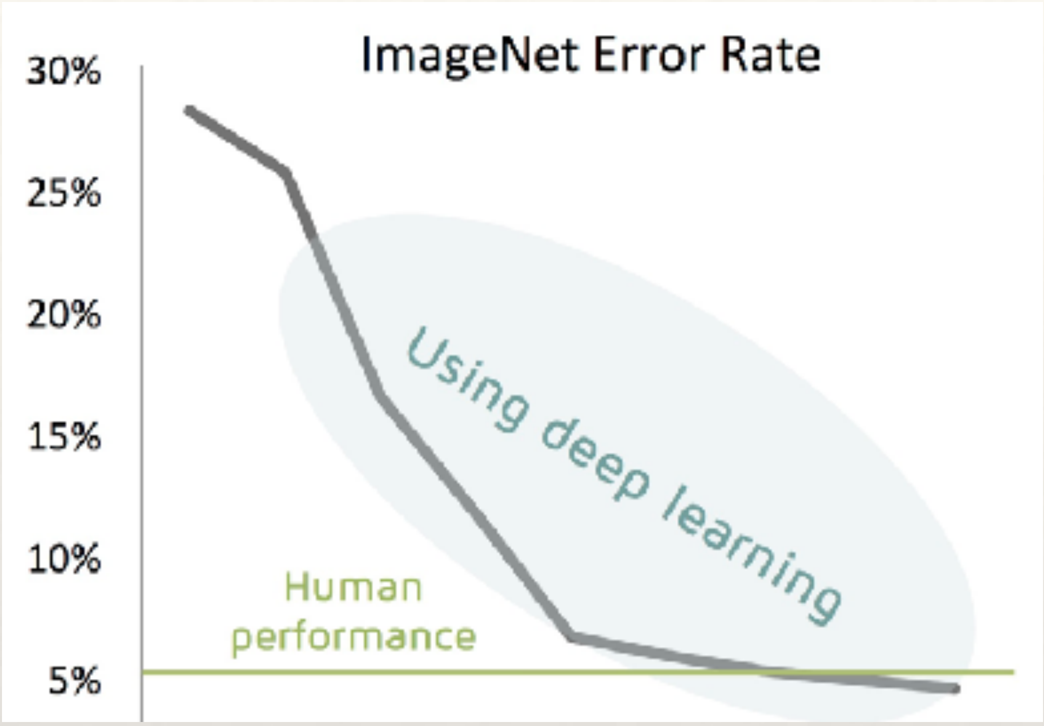
Johannes Bjerva — j.bjerva@rug.nl — 08/12/2016

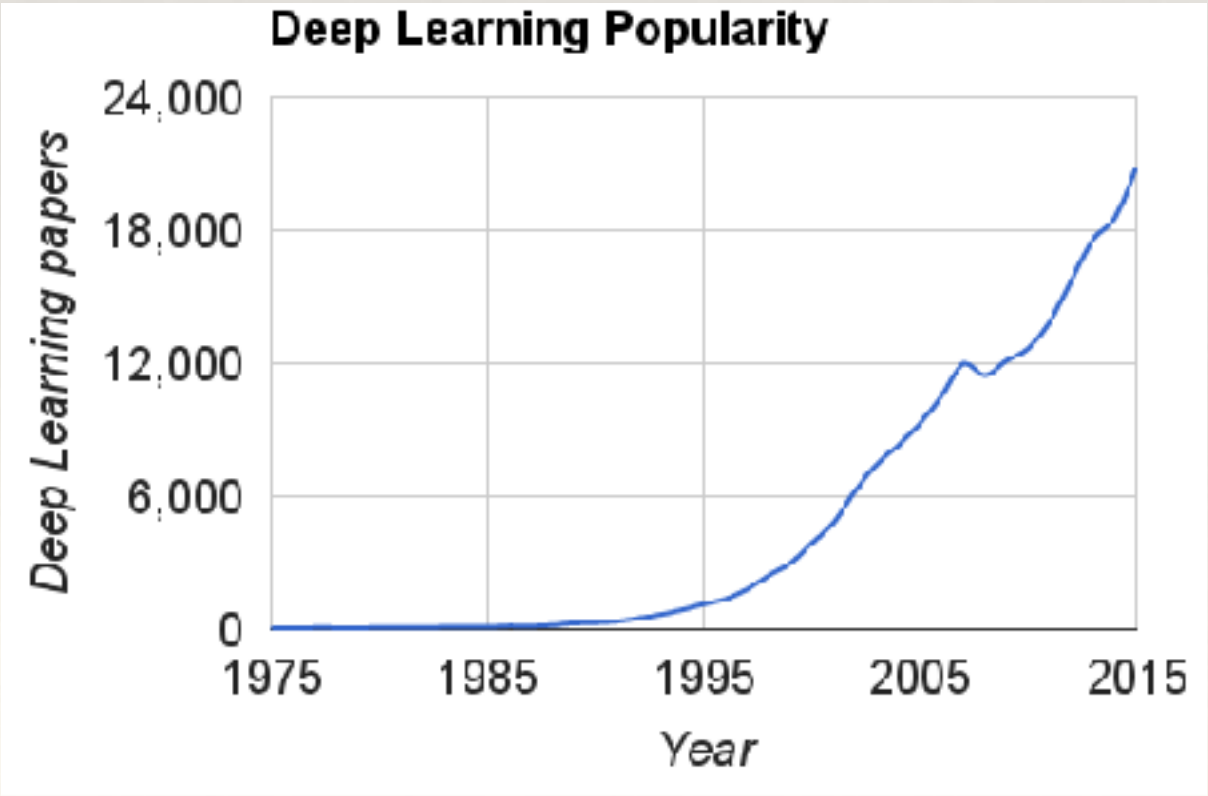
Semantic Analysis with Deep Neural Networks

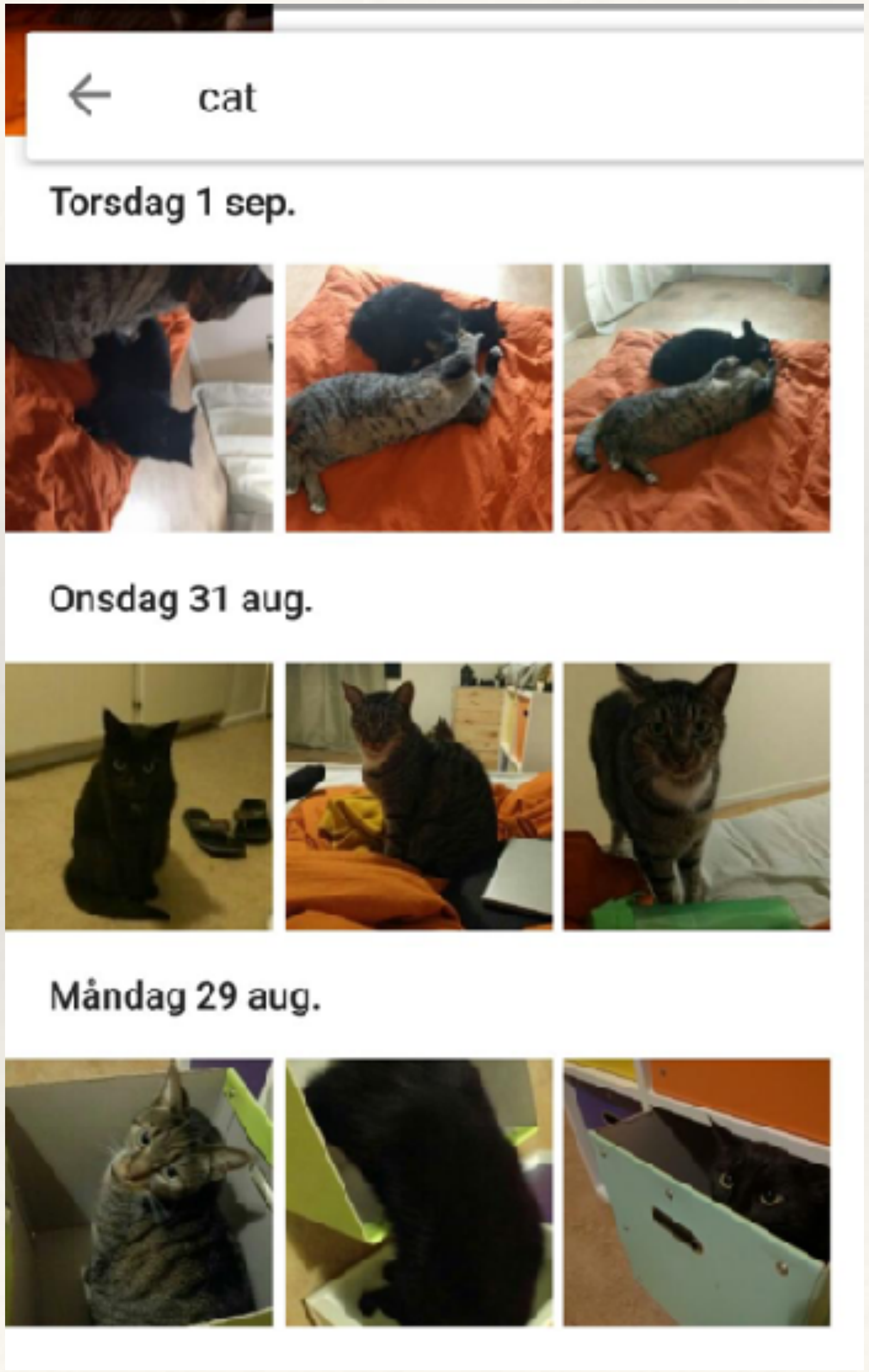
university of groningen

Deep Learning Overview

Why Deep Learning?





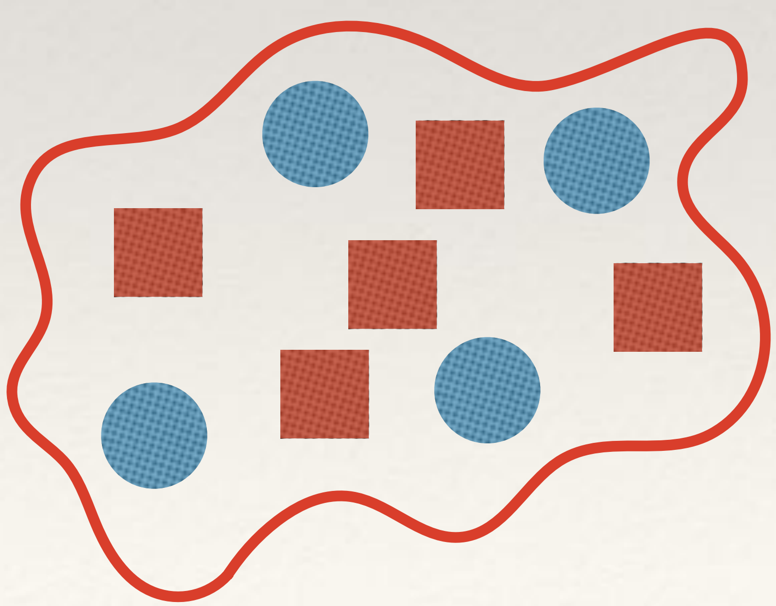


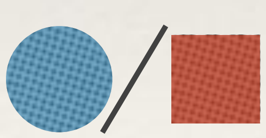
What is Machine Learning?

"[Machine Learning] gives computers the ability to learn without being explicitly programmed"

— *Arthur Samuel, 1959*

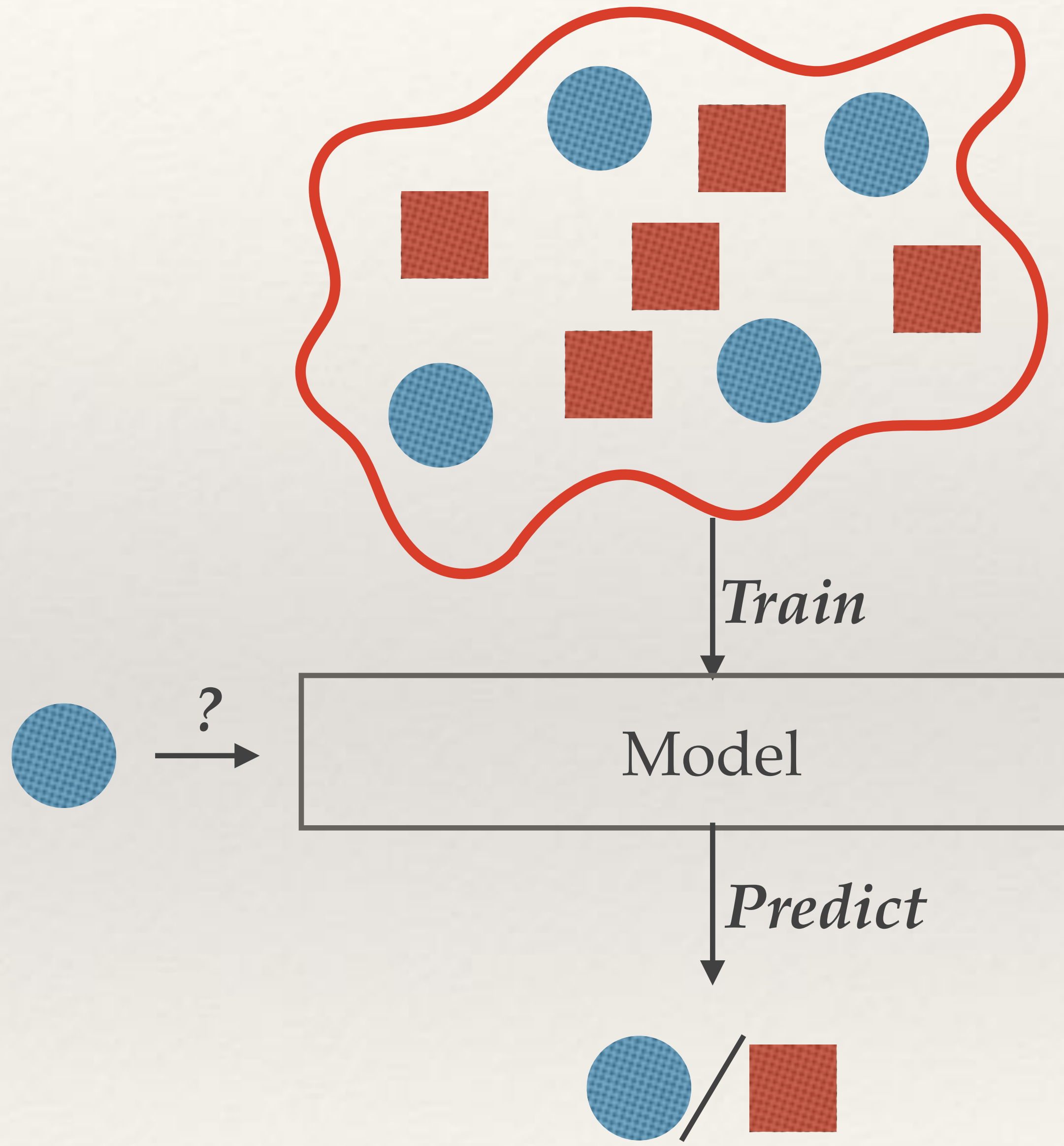
Annotated data:



Task:  ?

What is Machine Learning?

- Task: Part-of-Speech tagging
- Performance: e.g. accuracy
- Data: Annotated corpus

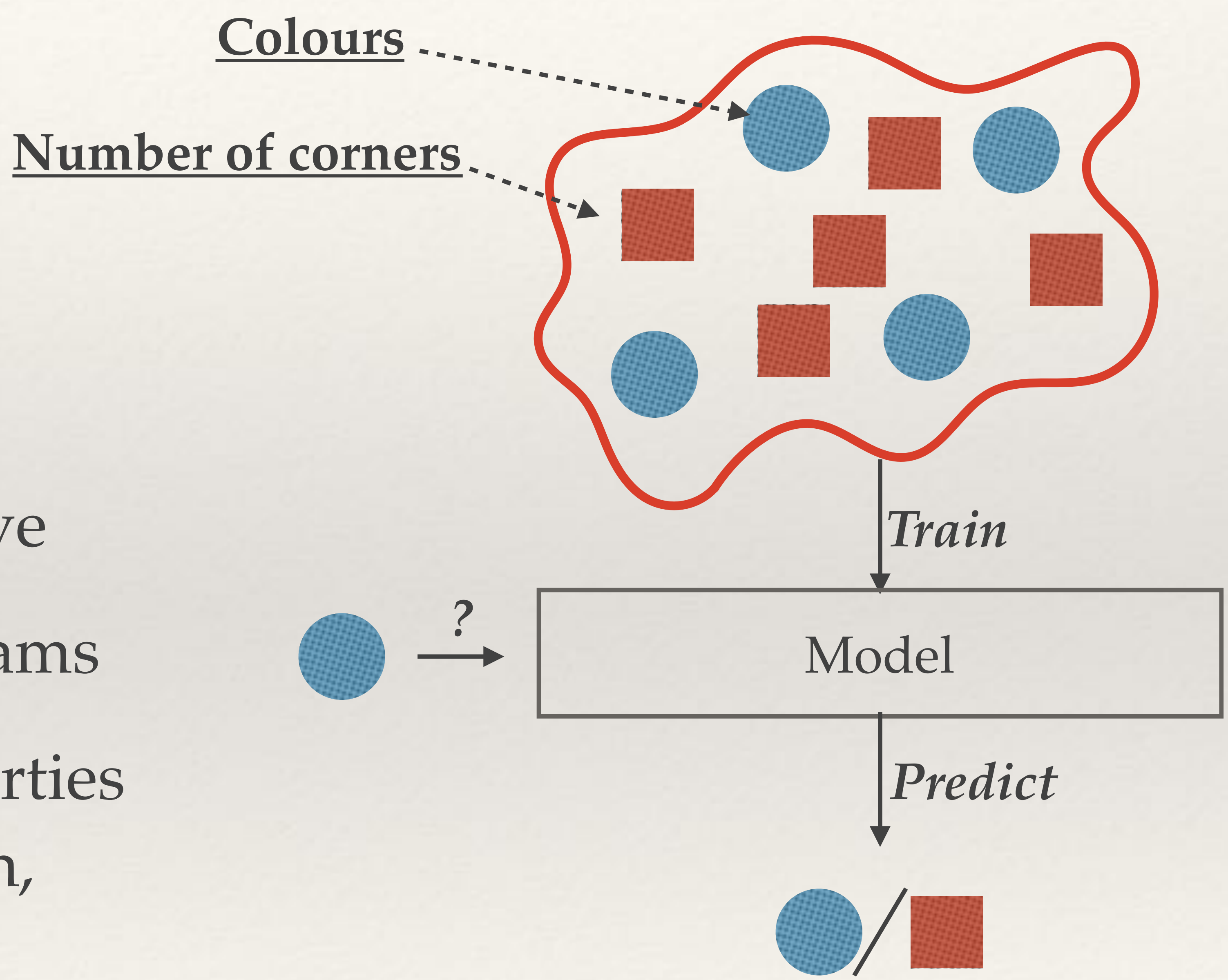


Demo!

What does the computer learn from?

Features!

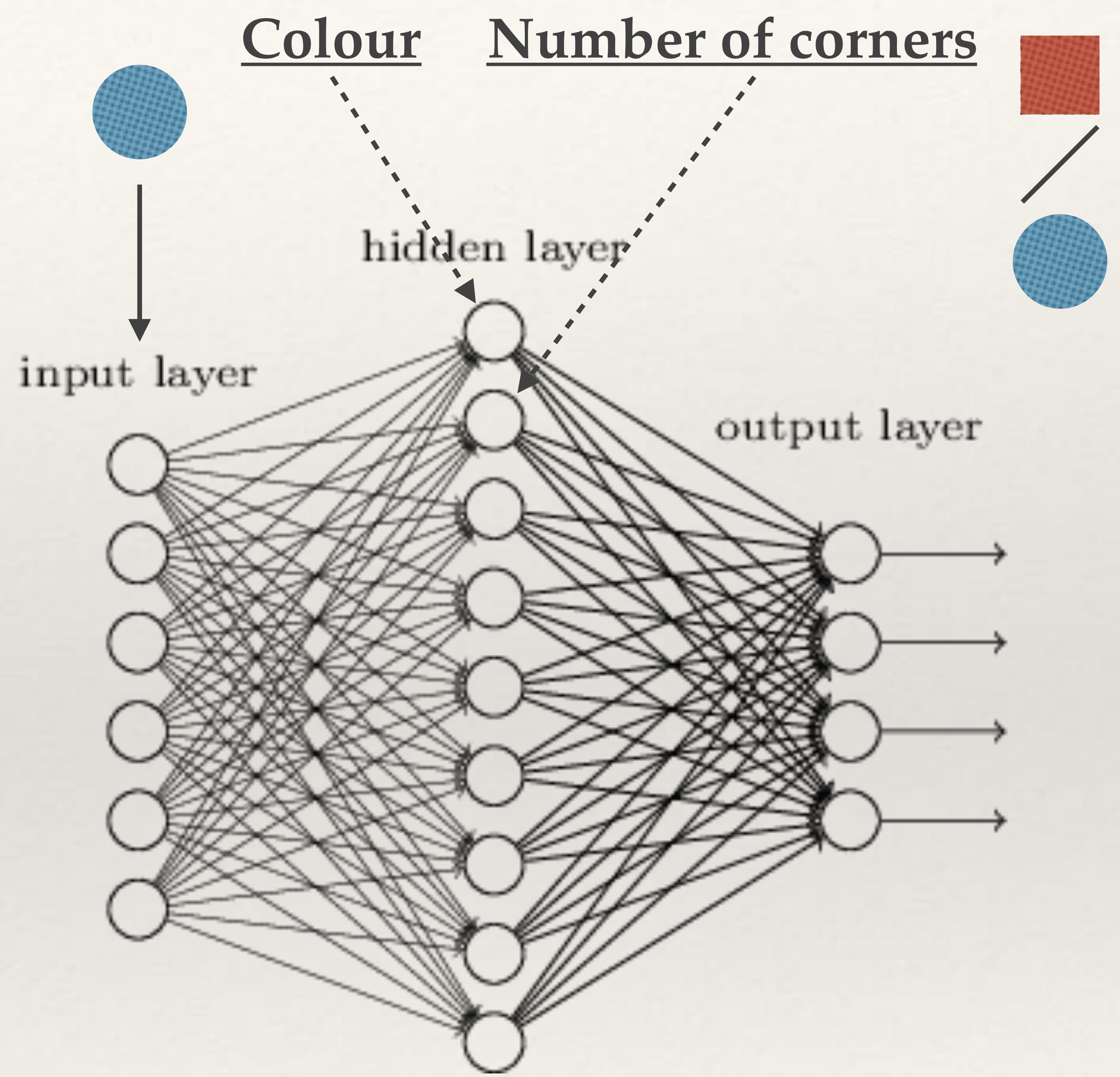
- Hand-coded
  - Time consuming
  - Not necessarily effective
- Word and character n-grams
- Relevant linguistic properties (e.g. affixes, capitalisation, root form)



What is a neural network?

- Biologically *inspired*

1. Take an input
2. Learn feature representations
3. Predict output
4. Self-correct if output is wrong
5. Repeat!

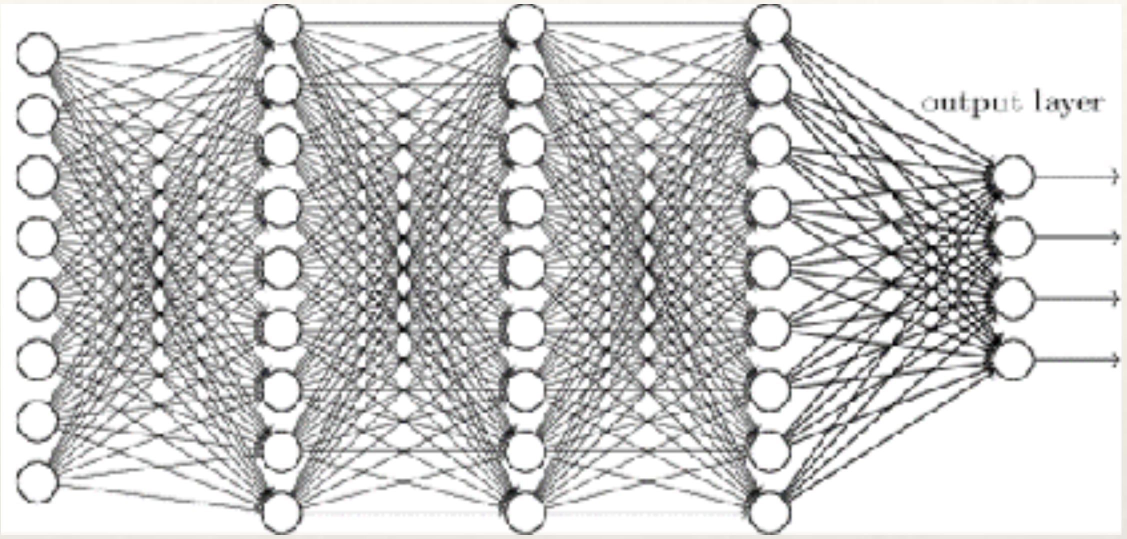


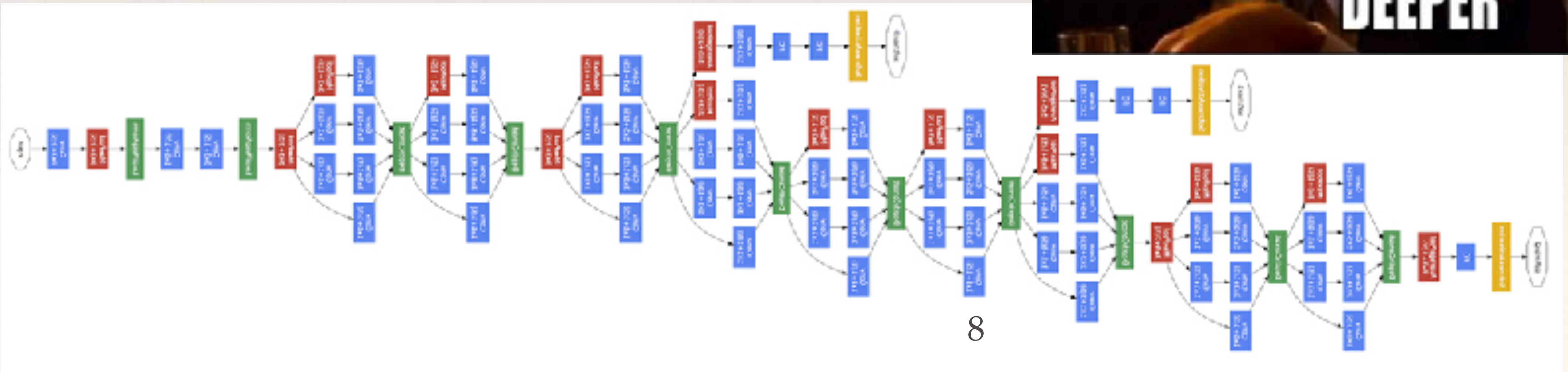
What is Deep Learning?

- Deep Neural Networks
- Automatically combine simple features into complex features
- Deeper is (often) better

Demo

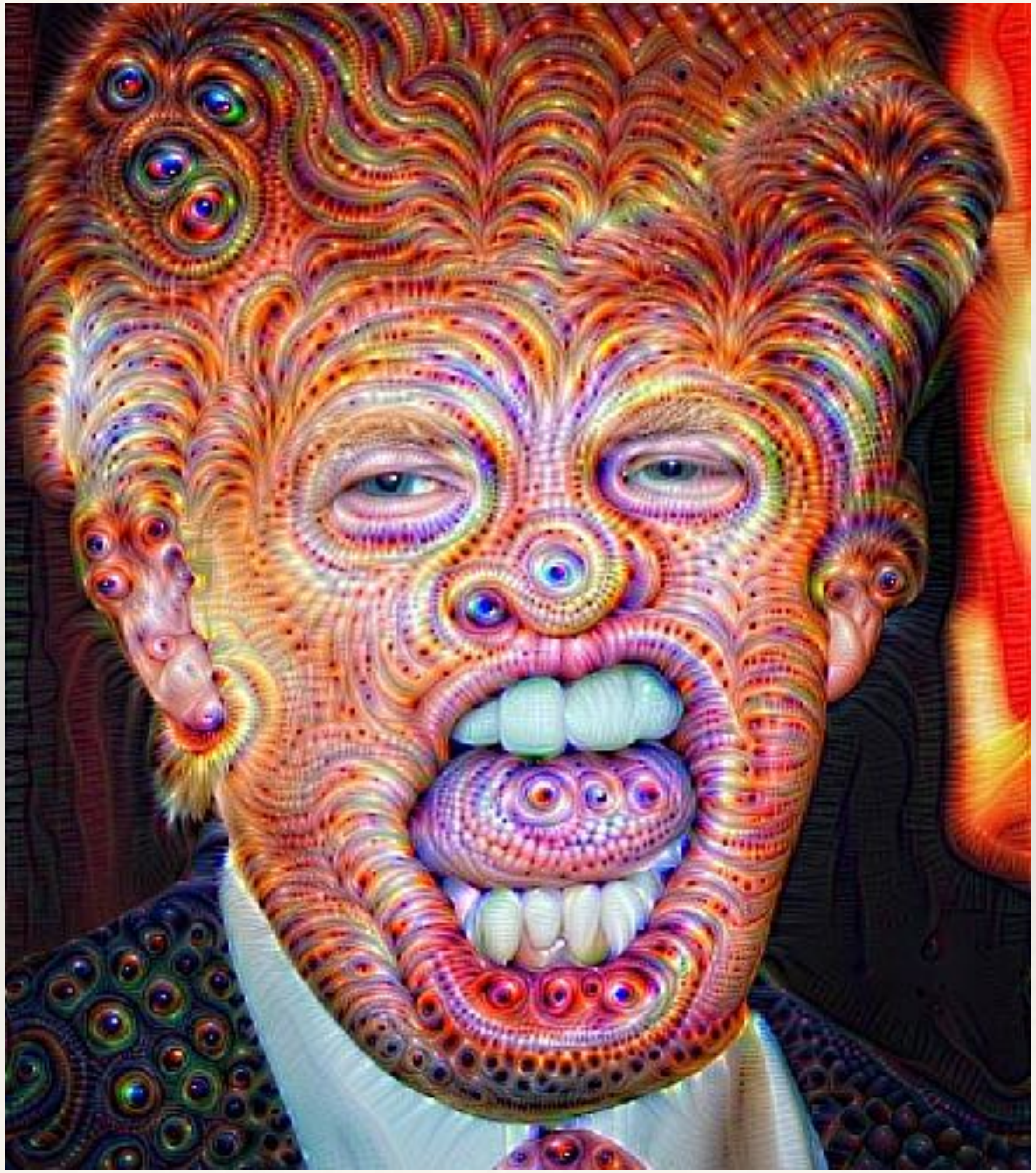
playground.tensorflow.org





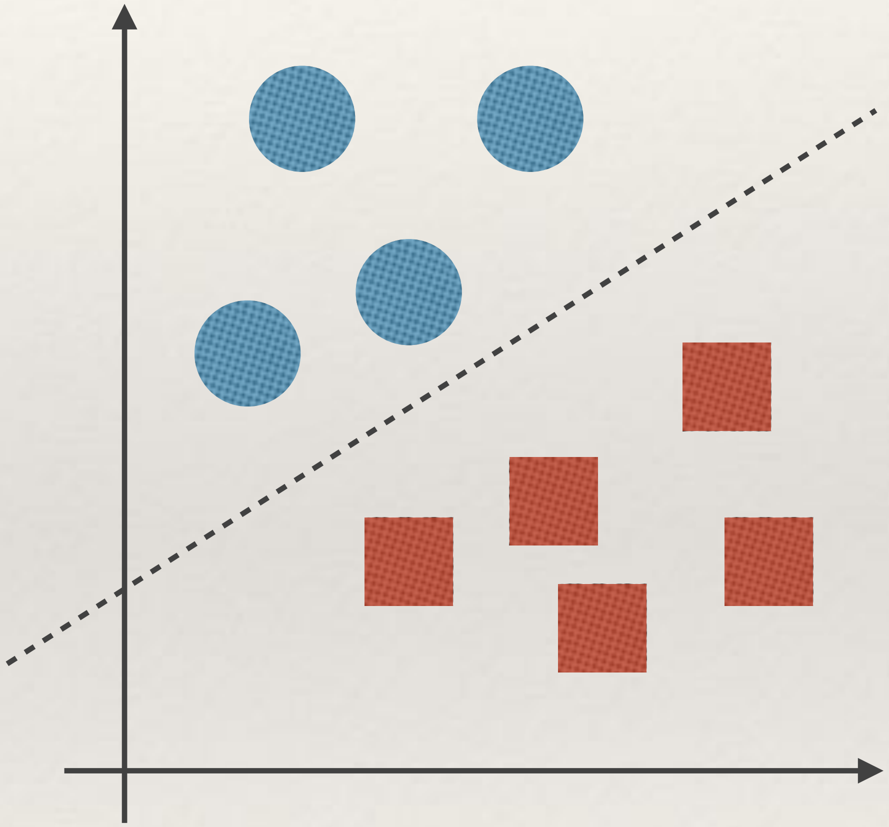
What can Deep Learning do?

- Make psychedelic images!
- Google QuickDraw: https://quickdraw.withgoogle.com
- Text-to-speech: https://deepmind.com/blog/wavenet-generative-model-raw-audio/
- Generate hand-writing: http://www.cs.toronto.edu/~graves/handwriting.cgi
- *Currently the most successful approach to many NLP problems*

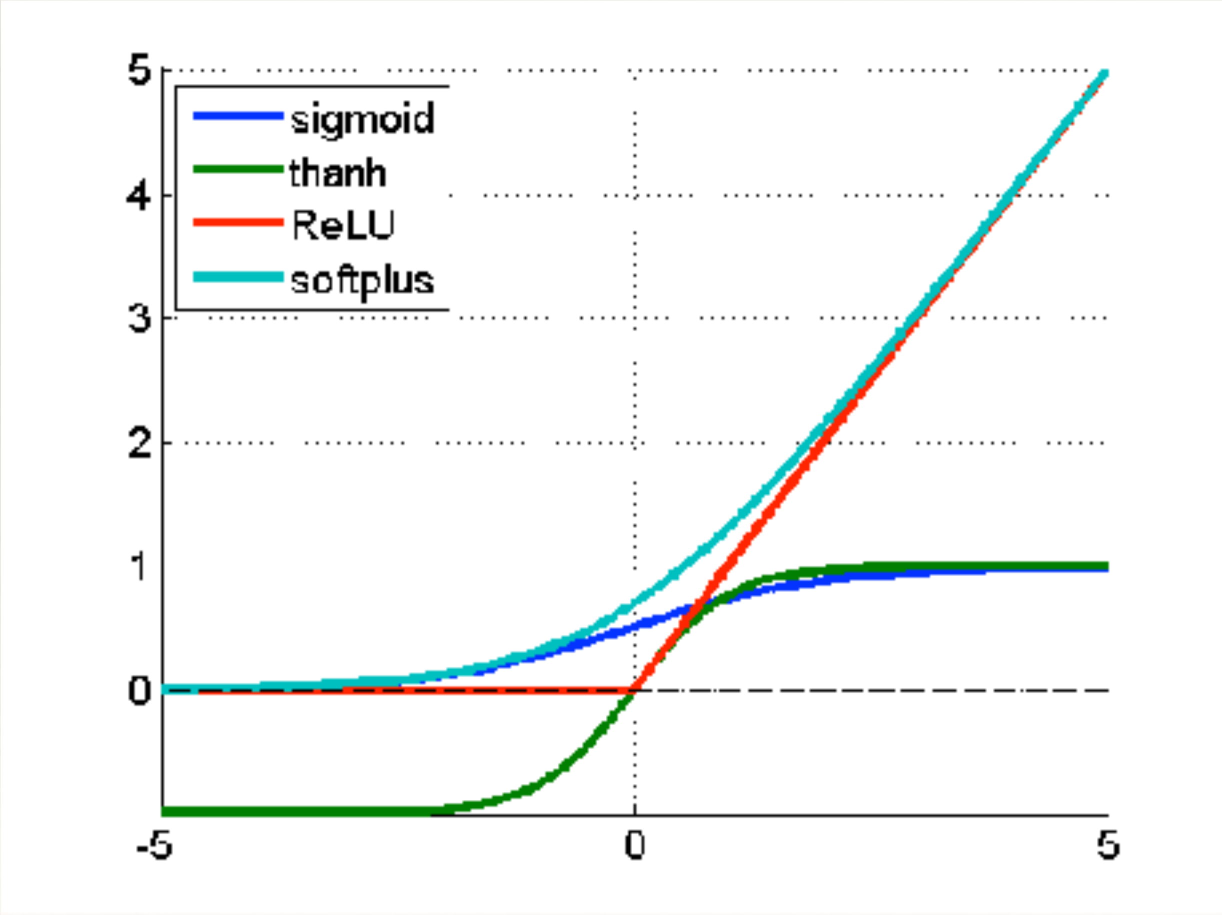


Deep Learning for everything?

- Not a silver bullet
- Simple problems do not require fancy methods



Deep Learning and the Human Brain



- In Computational Linguistics:
  Not an attempt to model the brain
- Some inspiration is useful (ReLU)

Why are neural networks back?

- More computational power (GPUs)
- More data
- Better algorithms/architectures

Semantic Analysis with Deep Neural Networks

Semantic Analysis

- Parallel Meaning Bank
  http://pmb.let.rug.nl/explorer/explore.php
- English, Dutch, German, Italian
- **Goal:**
  Parallel corpus with Discourse Representation Structures for all languages
- About 11 million tokens

Chapter I: Semantic Tagging

- Multilingual Semantic Parsing
- Experimenting with different Neural Network architectures

Semantic Tags – Motivation

- POS tags: insufficient and irrelevant information
- Insufficient:
    - *every* (DT / univ. quant.)
    - *no* (DT / neg.)
    - *some* (DT / exist. quant.)
- Irrelevant:
    - *walks* (VBZ / pres. simpl.)
    - *walk* (VBP / pres. simpl.)

Semantic Tags – Example

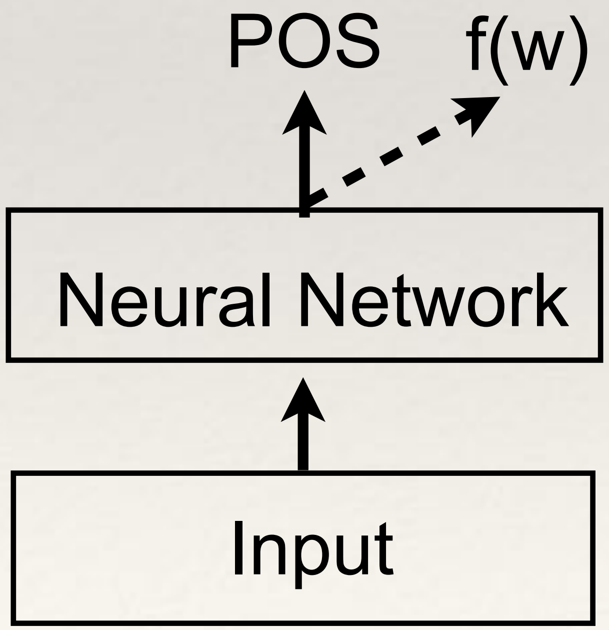
Tokens:	These	cats	live	in	that	house	.
Sem-tags:	PRX	CON	ENS	REL	DST	CON	NIL
UD-POS:	DET	NOUN	VERB	ADP	DET	NOUN	PUNCT

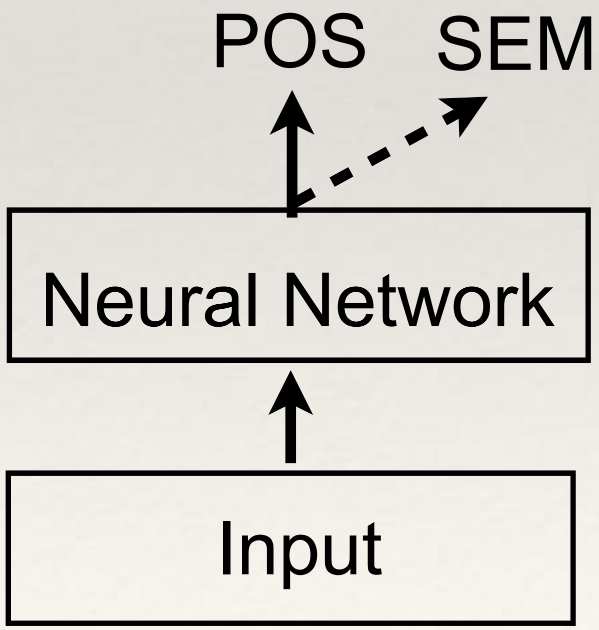
Semantic Tags – Overview

- About 75 tags
- Abstract over POS and NE tags
- Includes categories for negation, modality and quantification
- Generalises over languages (en, de, nl, it)

Auxiliary tasks

- Giving the NN more work to do
- Informing the NN of what additional task might be helpful to learn
- Word frequencies for POS tagging
- This work:
  Semantic tags for POS tagging





[Plank et al., 2016]

Results

	Baselines				Basic CNN			ResNet		
	MFC	TNT	Bi-LSTM	Bi-GRU	$\vec{c}$	$\vec{c} \wedge \vec{w}$	+AUX	$\vec{c}$	$\vec{c} \wedge \vec{w}$	+AUX
Semtag Silver	84.64	92.09	94.98	94.26	91.39	94.63	94.53	94.39	**95.14**	94.23
Semtag Gold	77.39	80.73	82.96	80.26	69.21	76.83	80.73	76.89	**83.64**	74.84

Table 1: Experiment results on semtag (ST) test sets (% accuracy). MFC indicates the per-word most frequent class baseline, TNT indicates the TNT tagger, and Bi-LSTM indicates the system by Plank et al. (2016). Bi-GRU indicates the $\vec{w}$ only baseline. $\vec{w}$ indicates usage of word representations, $\vec{c}$ indicates usage of character representations. The +AUX column indicates the usage of an auxiliary loss.

	Baselines				Basic CNN			ResNet		
	MFC	TNT	Bi-LSTM	Bi-GRU	$\vec{c}$	$\vec{c} \wedge \vec{w}$	+AUX	$\vec{c}$	$\vec{c} \wedge \vec{w}$	+AUX
UD v1.2	85.06	92.66	95.17	94.39	77.63	94.68	95.19	92.65	94.92	**95.71**
UD v1.3	85.07	92.69	95.04	94.32	77.51	94.89	95.34	92.63	94.88	**95.67**

Table 2: Experiment results on Universal Dependencies (UD) test sets (% accuracy).

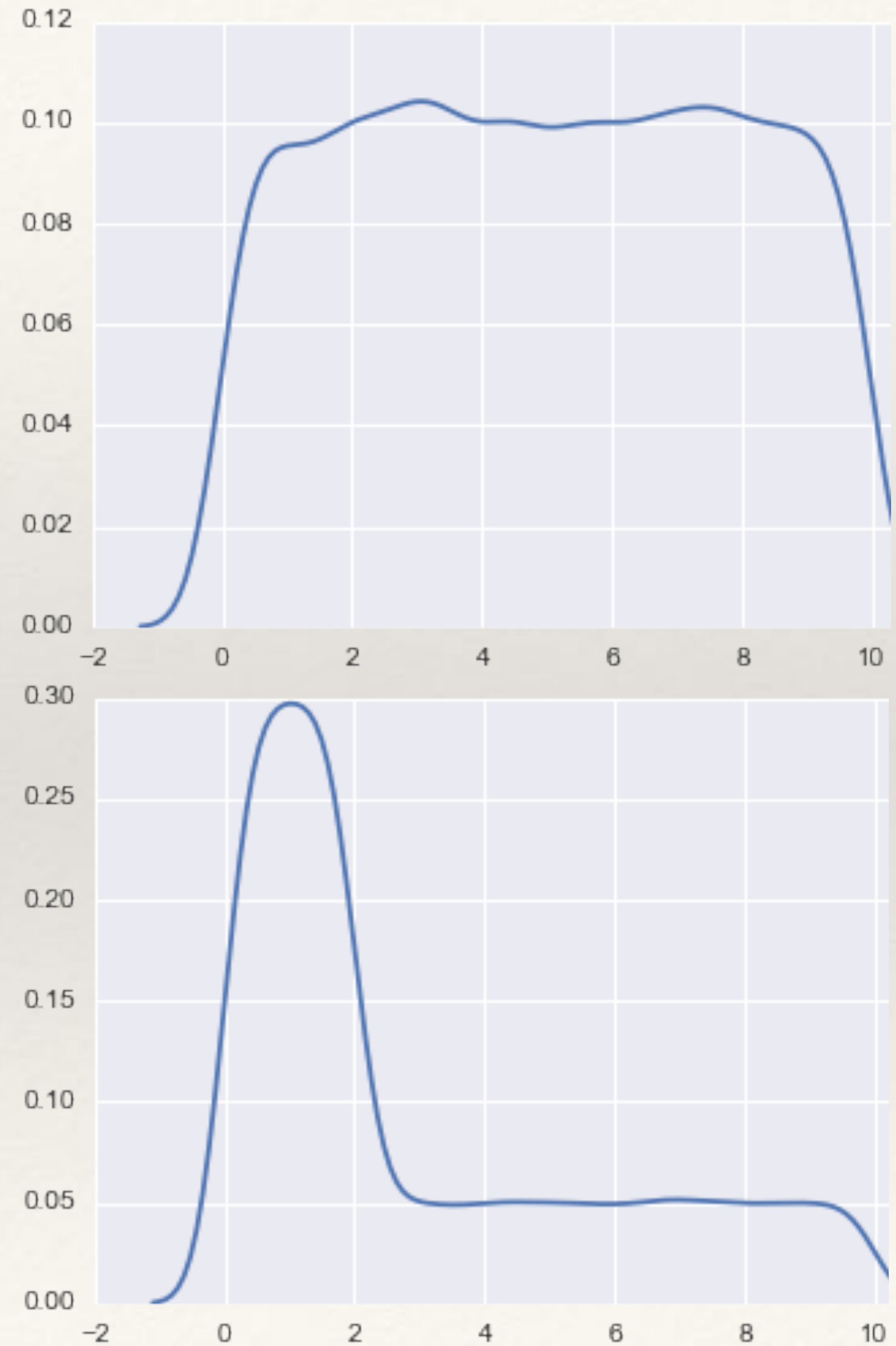
[Bjerva et al., 2016]

Chapter II: Multitask Learning

When and why does Multitask Learning help?

When does MTL help?

- “[…] when the label distribution is compact and uniform”
- —> High entropy, few labels



Is 'high entropy' sufficient?

Tokens:	These	cats	live	in	that	house	.
Sem-tags:	PRX	CON	ENS	REL	DST	CON	NIL
UD-POS:	DET	NOUN	VERB	ADP	DET	NOUN	PUNCT

Is 'high entropy' sufficient?

Tokens:	These	cats	live	in	that	house	.
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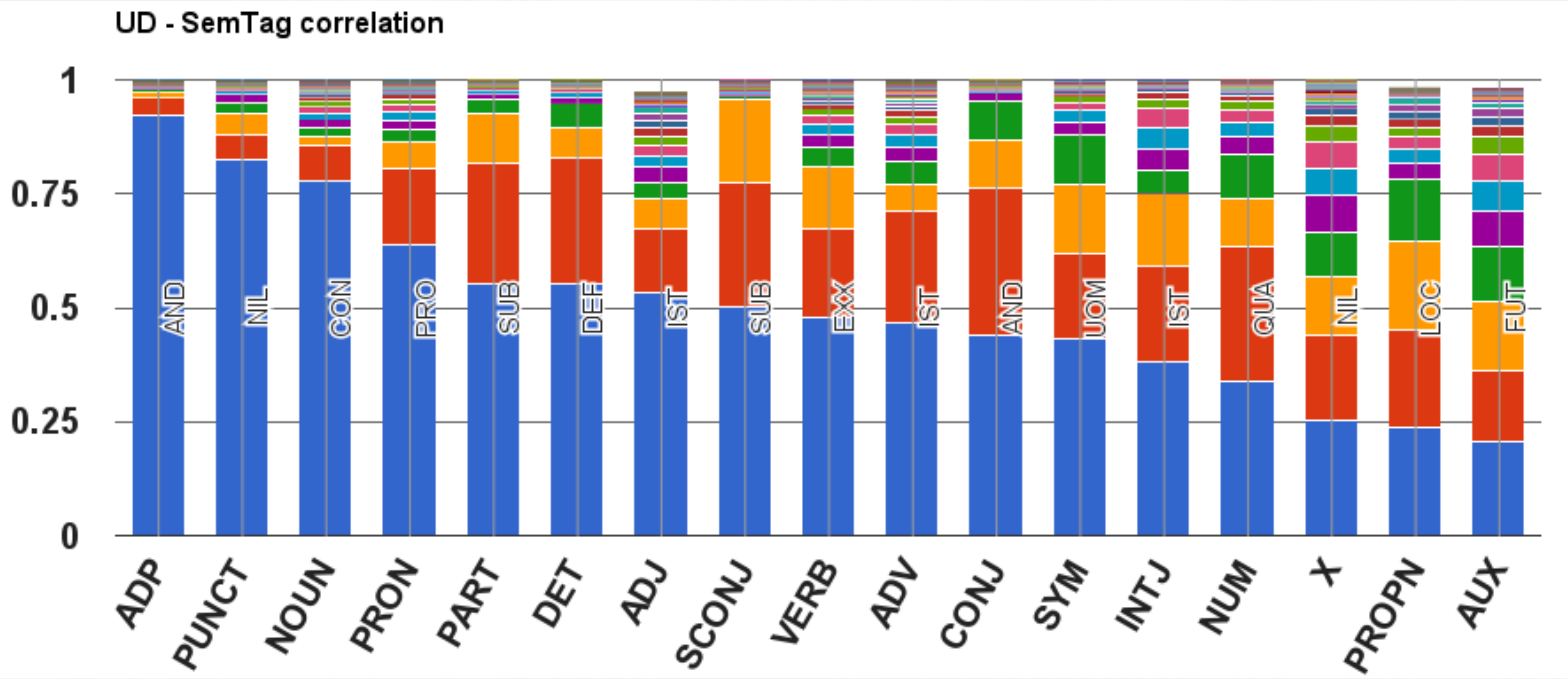
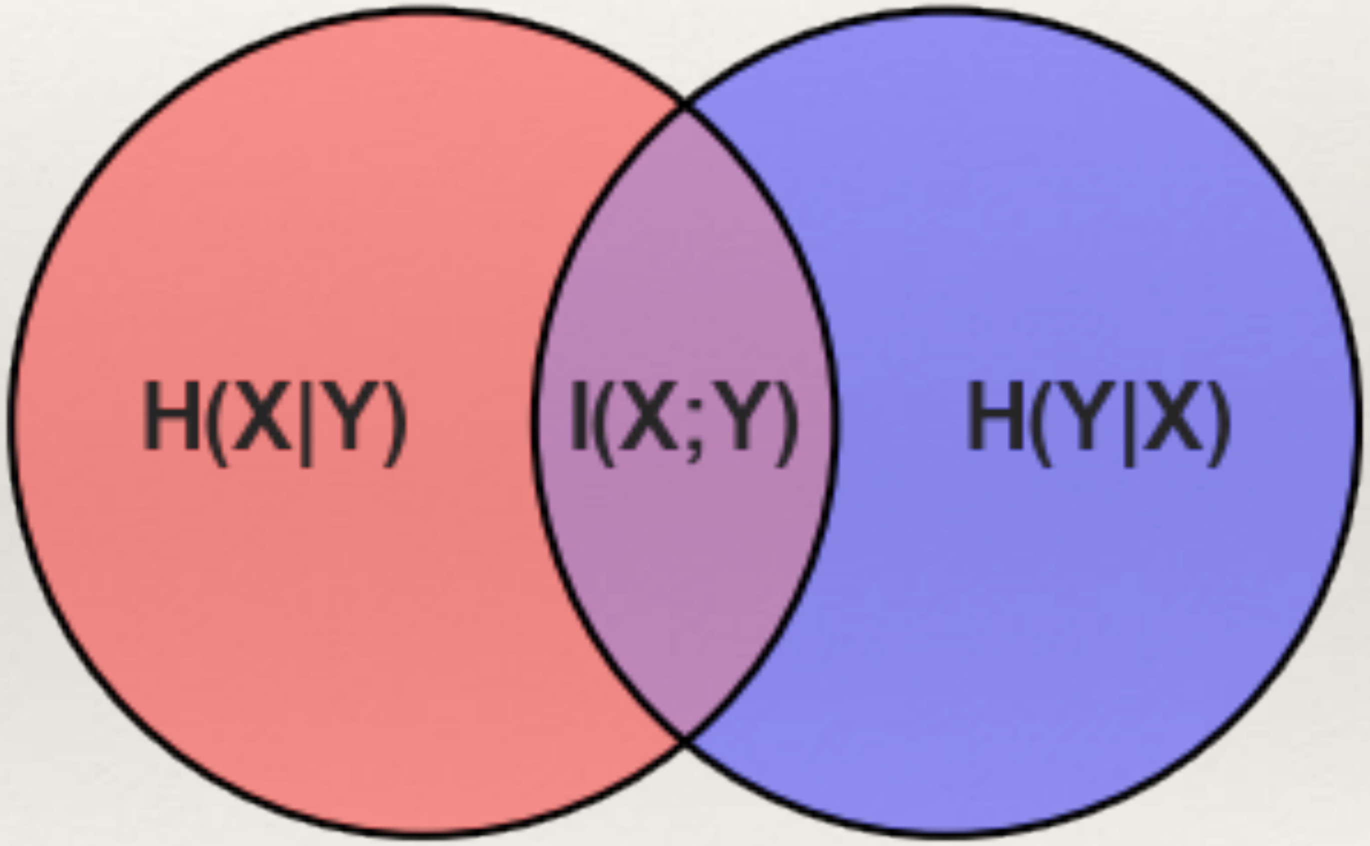
Tagset correlations



Information-theoretic Measures

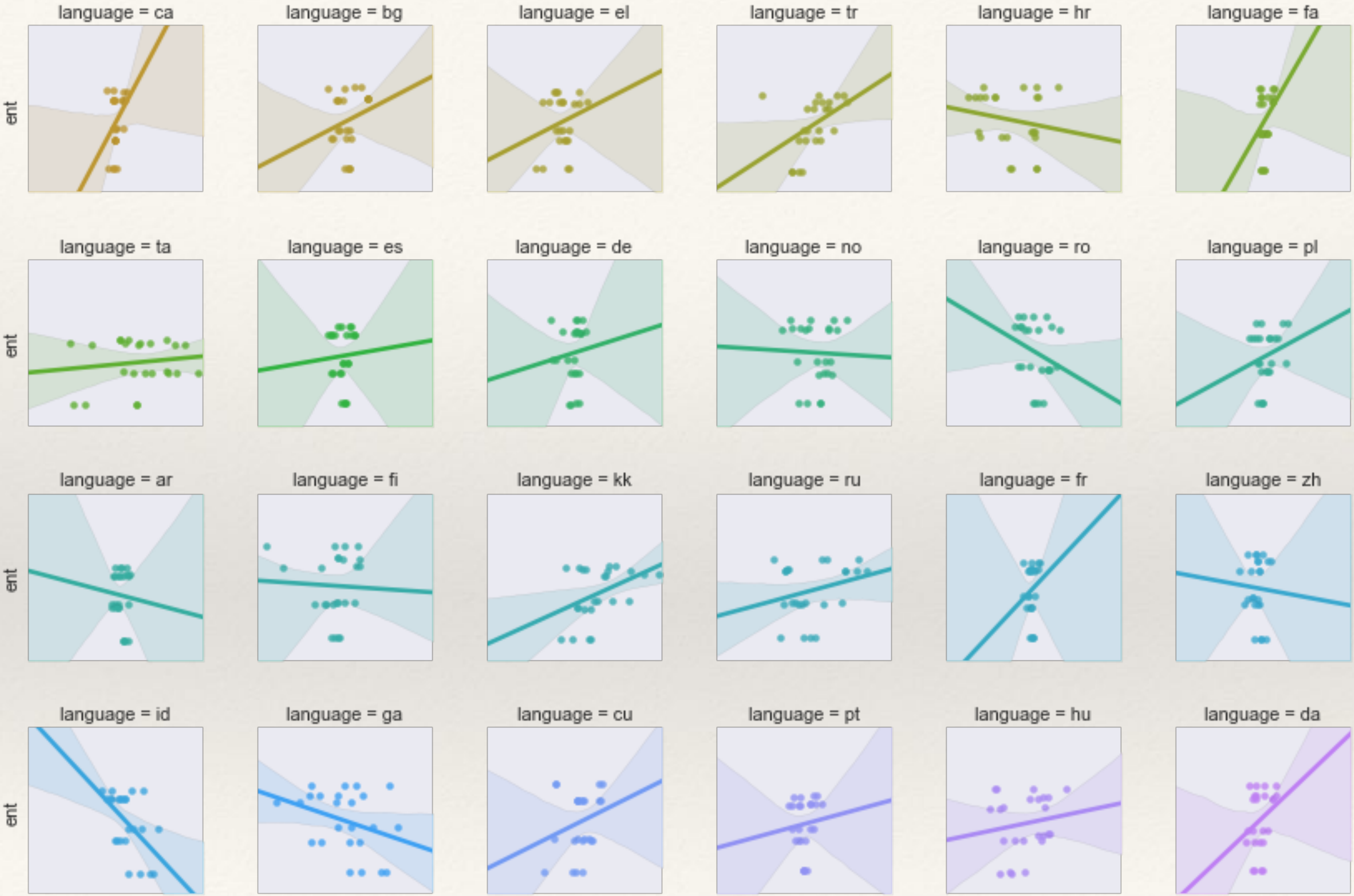
- Calculating tagset correlations:
  - Conditional Entropy
  - Mutual Information



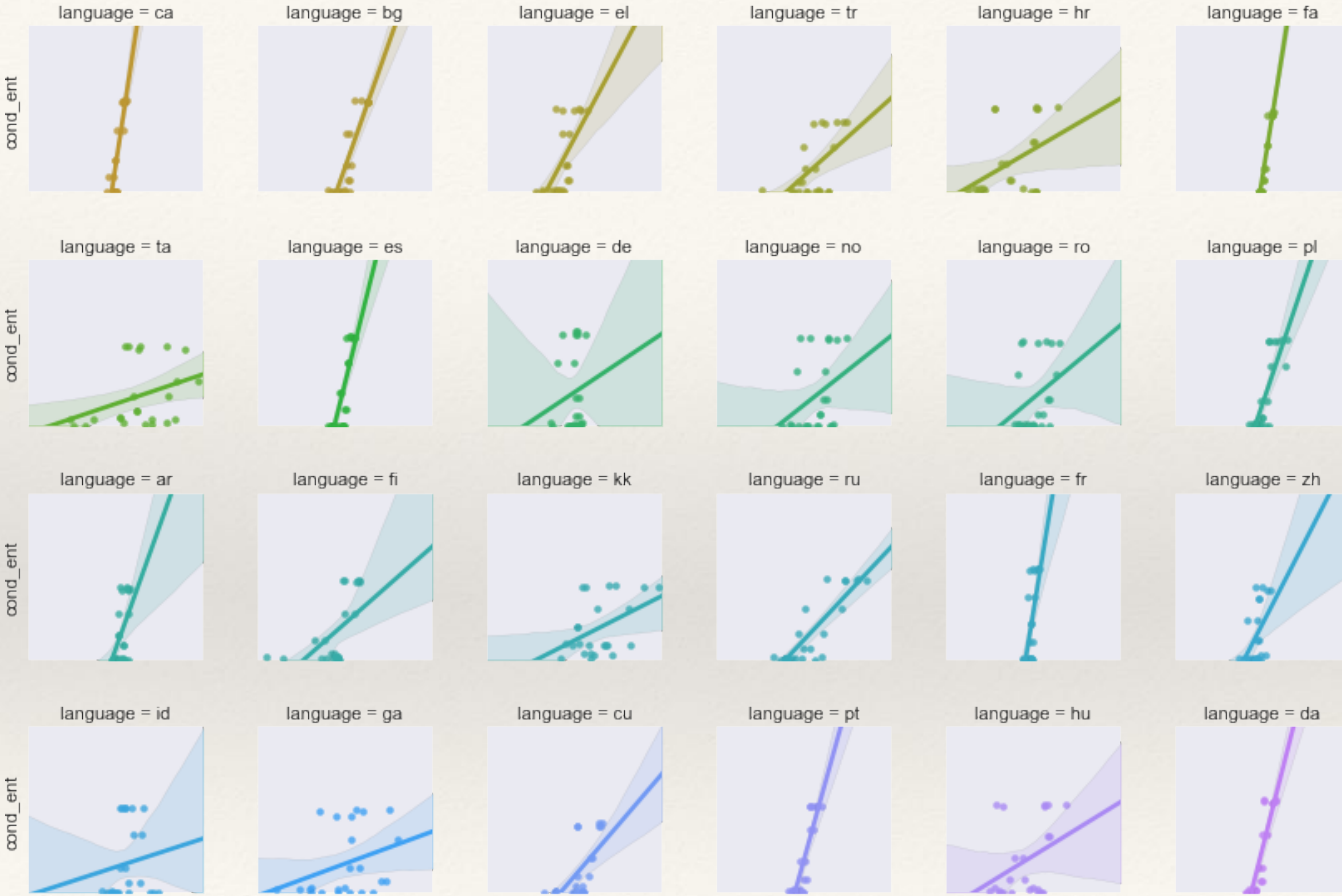
Correlation with Auxiliary Task Effectivity

Conditional Entropy and Mutual Information both correlate far better than entropy!

Auxiliary task	$\rho(\Delta_{acc}, H(Y))$	$\rho(\Delta_{acc}, H(Y\|X))$	$\rho(\Delta_{acc}, I(X;Y))$
Supertagging (Identity)	-0.06 ($p=0.214$)	0.12 ($p=0.013$)	0.08 ($p=0.114$)
Supertagging (Overlap)	0.07 ($p=0.127$)	0.27 ($p<0.001$)	**0.43 ($p\ll0.001$)**
Supertagging (Disjunct)	0.08 ($p=0.101$)	0.25 ($p<0.001$)	**0.41 ($p\ll0.001$)**



Change in accuracy (x) vs. Entropy (y)



Change in accuracy (x) vs. Mutual Information (y)

Remaining chapters

- Chapter III: Multilingual Learning
- Chapter IV: Semantic Similarity between Words and Sentences (SemEval Shared Tasks)
- Chapter V: Dataset Augmentation