

DISCOVERY OF NATURAL LANGUAGE CONCEPTS IN INDIVIDUAL UNITS OF CNNs

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<https://qdata.github.io/deep2Read/>

Motivation:

- Although deep convolutional networks have achieved improved performance in many natural language tasks, they have been treated as black boxes because they are difficult to interpret.
- Especially, little is known about how they represent language in their intermediate layers.
- Because of their lack of interpretability, deep models are often regarded as hard to debug and unreliable for deployment.
- They also prevent the user from learning about how to make better decisions based on the model's outputs.

Related Work:

1. Zhou et al. (2015): Object Detectors Emerge in Deep Scene CNNs.
1. Erhan et al. (2009): Visualizing Higher-layer Features of a Deep Network.
1. Olah et al. (2017): Feature Visualization.
1. Simonyan et al. (2013): Visualising Image Classification Models and Saliency maps.
1. Radford et al. (2017): Concept of sentiment aligned to a particular unit.

Background:

- **Character level CNN:** Represent each character as a one-hot encoded vector.
- **1D Convolution:** Convolution takes place in only one direction. In NLP the direction is the time axis.
- **Unit:** Each channel in convolutional representation.
- **Natural Language Concepts:** Grammatical units of natural language that preserve meanings; i.e. morphemes, words, and phrases.

Claim / Target Task:

The units of deep CNNs learned in NLP tasks could act as a natural language concept detector.

Top K Activated Sentences Per Unit:

- Given a layer and sentence $s \in S$, let $A_u^l(s)$ denote the activation of unit u at spatial location l .
- Then, for unit u , average activations over all spatial locations as:
$$a_u(s) = \frac{1}{Z} \sum_l A_u^l(s)$$
, where Z is a normalizer.
- Retrieve top K training sentences per unit with the highest mean activation a_u .

Unit 108: **legal**, **law**, **legislative**

- Better **legal** protection for accident victims.
- These rights are guaranteed under **law**.
- This should be guaranteed by **law**.
- This **legislative** proposal is unusual.
- Animal feed must be safe for animal health.

Unit 711: **should**, **would**, **not**, **can**

- That **would** **not** be democratic.
- That **would** be cheap and it **would** **not** be right.
- This is **not** how it **should** be in a democracy.
- I hope that you **would** **not** want that!
- Europe **cannot** and must **not** tolerate this.

Figure 1: We discover the most activated sentences and aligned concepts to the units in hidden representations of deep convolutional networks. Aligned concepts appear frequently in most activated sentences, implying that those units respond selectively to specific natural language concepts.

Identifying Concepts:

1. Parse each of top K sentences with a constituency parser (Kitaev & Klein, 2018).
1. From sentence “John hit the balls”, we obtain candidate concepts as {John, hit, the, balls, the balls, hit the balls, John hit the balls}.
1. Also break each word into morphemes using a morphological analysis tool (Virpioja et al., 2013) and add them to candidate concepts (e.g. from word “balls”, we obtain morphemes {ball, s}).

$C_u = \{c_1, \dots, c_N\}$, where N is the number of candidate concepts of the unit.

Measuring Contribution of each Concept:

1. For normalizing, create a synthetic sentence by replicating each candidate concept so that its length is identical to the average length of all training sentences.
(e.g. candidate concept “the ball” is replicated as “the ball the ball the ball...”)
1. Degree of alignment (DoA) between a candidate concept “ c_n ” and a unit “ u ” :

$$\mathbf{DoA}_{u,cn} = \mathbf{a}_u(\mathbf{r}_n)$$

1. DoA measures the extent to unit u ’s activation is sensitive to the presence of candidate concept c_n .
1. Larger the value suggests that candidate concept c_n is strongly aligned to unit u .
1. For each unit u , define a set of its aligned concepts $\mathbf{C}^*_u = \{\mathbf{c}^*_1, \dots, \mathbf{c}^*_M\}$ as M candidate concepts with the largest DoA values in C_u .

Datasets and Model Descriptions:

Dataset	Task	Model	# of Layers	# of Units
AG News	Ontology Classification	VDCNN	4	[64, 128, 256, 512]
DBpedia	Topic Classification	VDCNN	4	[64, 128, 256, 512]
Yelp Review	Polarity Classification	VDCNN	4	[64, 128, 256, 512]
WMT17' EN-DE	Translation	ByteNet	15	[1024] for all
WMT14' EN-FR	Translation	ByteNet	15	[1024] for all
WMT14' EN-CS	Translation	ByteNet	15	[1024] for all
EN-DE Europarl-v7	Translation	ByteNet	15	[1024] for all

Table 1: Datasets and model descriptions used in our analysis.

Evaluation of Concept Alignment:

Define the concept selectivity of a unit u , to a set of concepts C^*_u as follows:

$$Sel_u = \frac{\mu_+ - \mu_-}{\max_{s \in S} a_u(s) - \min_{s \in S} a_u(s)} \quad (2)$$

where S denotes all sentences in training set, and $\mu_+ = \frac{1}{|S_+|} \sum_{s \in S_+} a_u(s)$ is the average value of unit activation when forwarding a set of sentences S_+ , which is defined as one of the following:

replicate: S_+ contains the sentences created by replicating each concept in C^*_u .

one instance: S_+ contains just one instance of each concept in C^*_u .

inclusion: S_+ contains the training sentences that include at least one concept in C^*_u .

random: S_+ contains randomly sampled sentences from the training data.

In contrast, μ_- is the average value of unit activation when forwarding S_- , which consists of training sentences that do not include any concept in C^*_u .

Evaluation of Concept Alignment:

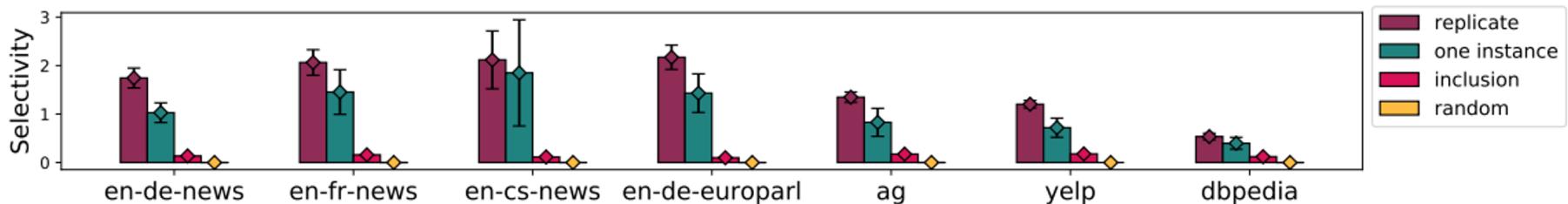


Figure 2: Mean and variance of selectivity values over all units in the learned representation for each dataset. Sentences including the concepts that our alignment method discovers always activate units significantly more than random sentences. See section 4.2 for details.

- Mean selectivity of the replicate set is the highest with a significant margin.
- Mean selectivity of the replicate set is higher than that of the one instance set, which implies that a unit's activation increases as its concepts appear more often in the input text.

Concept Alignment of Units:

Morpheme	Layer00, Unit 124: [#(,), #], [#]-	Layer00, Unit 53: [#]1999 [#]1969 [#]1992
	<ul style="list-style-type: none"> [COM]2001 24 CS0527/2001 2001/2207[COS] Exemptions will follow a two-stage procedure. Such exceptions were completely inappropriate. Exchange of views with microphones switched off [COM]2001 1 CS0007/2001 2001/0005[COD]) 	<ul style="list-style-type: none"> 19 august 1918 – 26 december 1999.. victor hernández cruz (born february 6 1949) is a puerto rican poet who in 1969 became the.. vicki schneider (born august 12 1957) is a republican member...
Word	Layer14, Unit 690: what who where	Layer01, Unit 19: soft software [#]wi
	<ul style="list-style-type: none"> Who gets what, how much and when? On what basis, when and how? Then we need to ask: where do we start? However, what should we do at this point? What I am wondering now is: where are they? 	<ul style="list-style-type: none"> qualcomm has inked a licensing agreement with Microsoft people soft wants its customers to get aggressive with software upgrades to increase efficiency. provide its customers with access to wi fi hotspots around.. realnetworks altered the software for market-leading ipod. apple lost one war to micro soft by not licensing its mac...
Phrase	Layer14, Unit 224: sure know aware	Layer01, Unit 33: stock google stocks
	<ul style="list-style-type: none"> Are you sure you are aware of our full potential? They know that and we know that. I am sure you will understand. I am sure you will do this. I am confident that we will find a solution. 	<ul style="list-style-type: none"> google has a new one for the labs - google suggest google has released google desktop search, ... google shares jumped 18% in their stock market debut... web search leader google inc. unveiled google scholar... new york (reuters) - stocks moving on thursday:...
	Layer 06, Unit 396: of this communication will communication	Layer03, Unit 244: very disappointing absolute worst place
	<ul style="list-style-type: none"> That is not the subject of this communication That is the purpose of this communication. I would like to ask the Commissioner for a reply. This is impossible without increasing efficiency. Will we be able to achieve this, Commissioner? 	<ul style="list-style-type: none"> very disappointing ordered a vegetarian entrée,... what the hell did i pay for?... the absolute worst place i have ever done business with! the is by far the worst restaurant i have ever been to... this place is a rip off!...
	(a) Translation (ByteNet)	(b) Classification (VDCNN)

Figure 3: Examples of top activated sentences and aligned concepts to some units in several encoding layers of ByteNet and VDCNN. For each unit, concepts and their presence in top K sentences are shown in the same color. [#] symbol denotes morpheme concepts. See section 4.3 for details.

Concept Distribution In Layers:

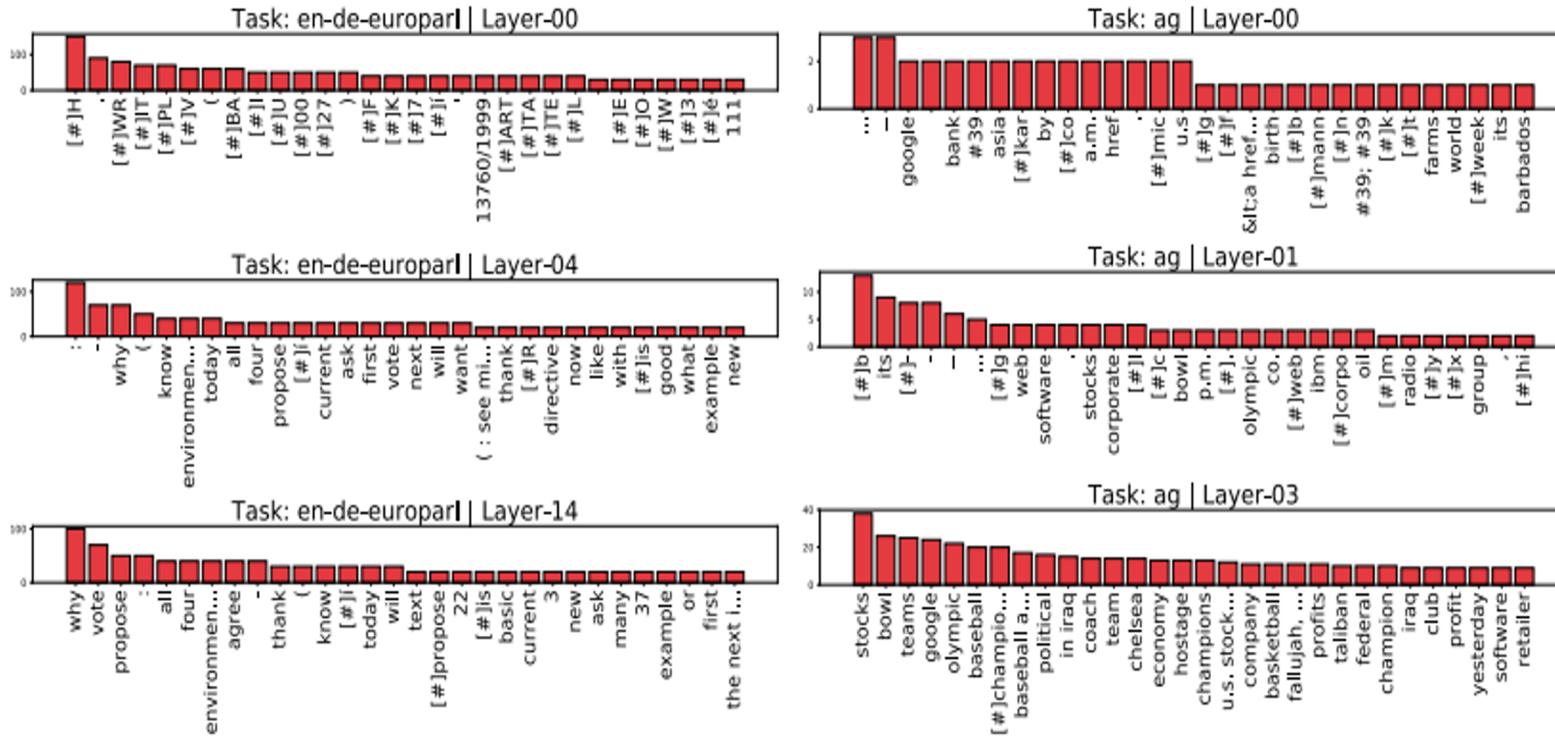


Figure 4: 30 concepts selected by the number of aligned units in three encoding layers of ByteNet learned on the Europarl translation dataset (left column) and VDCNN learned on AG-News (right column). [:#] symbol denotes morpheme concepts. See section 4.4 for details.

- Data and Task-specific concepts are likely to be aligned to many units 13

Concept Granularity Evolution with Layers:

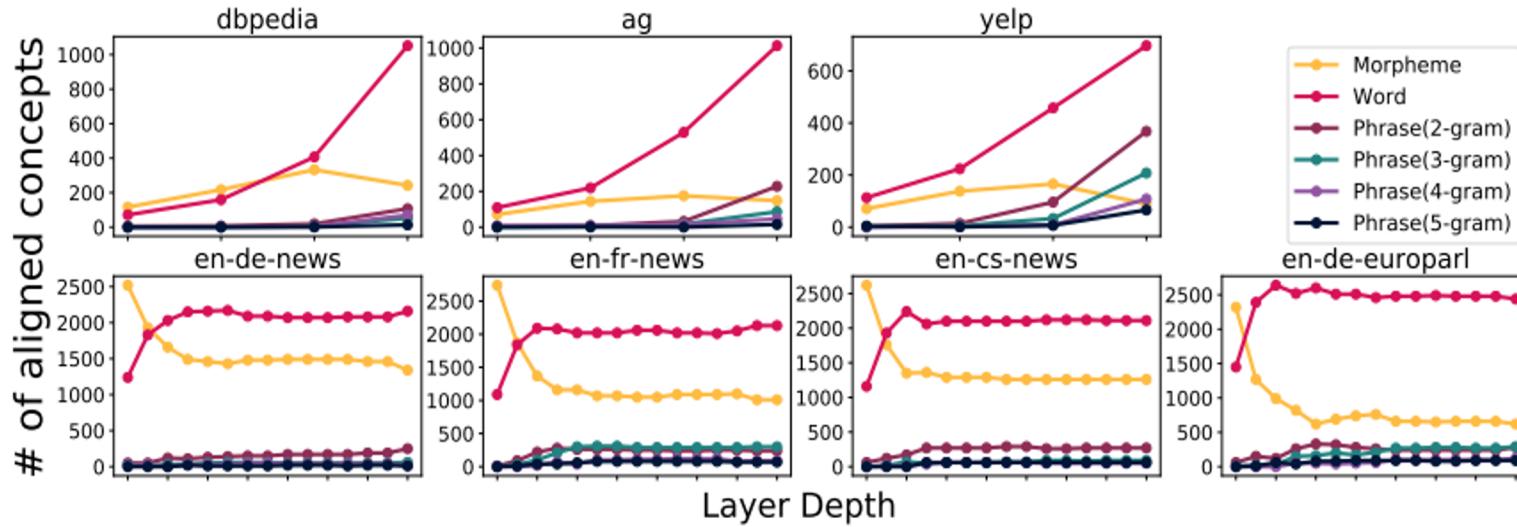


Figure 5: Aligned concepts are divided into six different levels of granularity: morphemes, words and N-gram phrases ($N = 2, 3, 4, 5$) and shown layerwise across multiple datasets and tasks. The number of units increases with layers in the classification models (*i.e.* [64, 128, 256, 512]), but in translation the number is constant (*i.e.* 1024) across all layers.

- In lower layers fewer phrase concepts but more morphemes and words are detected
- Concepts significantly change in shallower layers, but do not change much from middle to deeper layers.

Concept Granularity Evolution with Layers:

Why does concept granularity not evolve much in deeper layers?

1. Network is large enough so that the representations in the middle layers could be sufficiently informative to solve the task.

Retrained ByteNet from scratch while varying only layer depth of the encoder.

- Unlike in computer vision where deeper layers are usually more useful and discriminative.

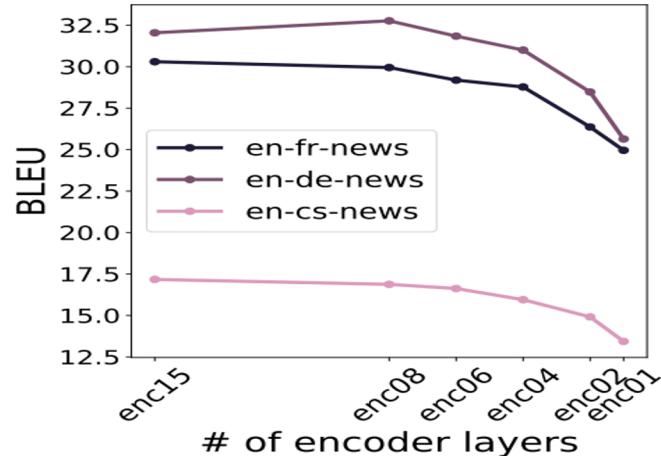


Figure 6: BLEU scores on the validation data for three translation models. We train ByteNet from scratch on each dataset by varying the number of encoder layers. 15

What Makes Certain Concepts Emerge More Than Others?

Why does concept granularity not evolve much in deeper layers?

1. The concepts with a higher frequency in training data may be aligned to more units.
1. The concepts that have more influence on the objective function (expected loss) may be aligned to more units.

$$\text{Delta of Expected Loss (DEL (c))} = \mathbb{E}_{s \in \mathcal{S}, y \in \mathcal{Y}} [\mathcal{L}(s, y)] - \mathbb{E}_{s \in \mathcal{S}, y \in \mathcal{Y}} [\mathcal{L}(\text{Occ}_c(s), y)]$$

where, S is a set of training sentences, and Y is the set of ground-truths, and L(s, y) is the loss function for the input sentence s and label y.

$\text{Occ}_c(s)$ is an occlusion of concept c in sentence s: replace concept c by dummy character tokens that have no meaning.

What Makes Certain Concepts Emerge More Than Others?

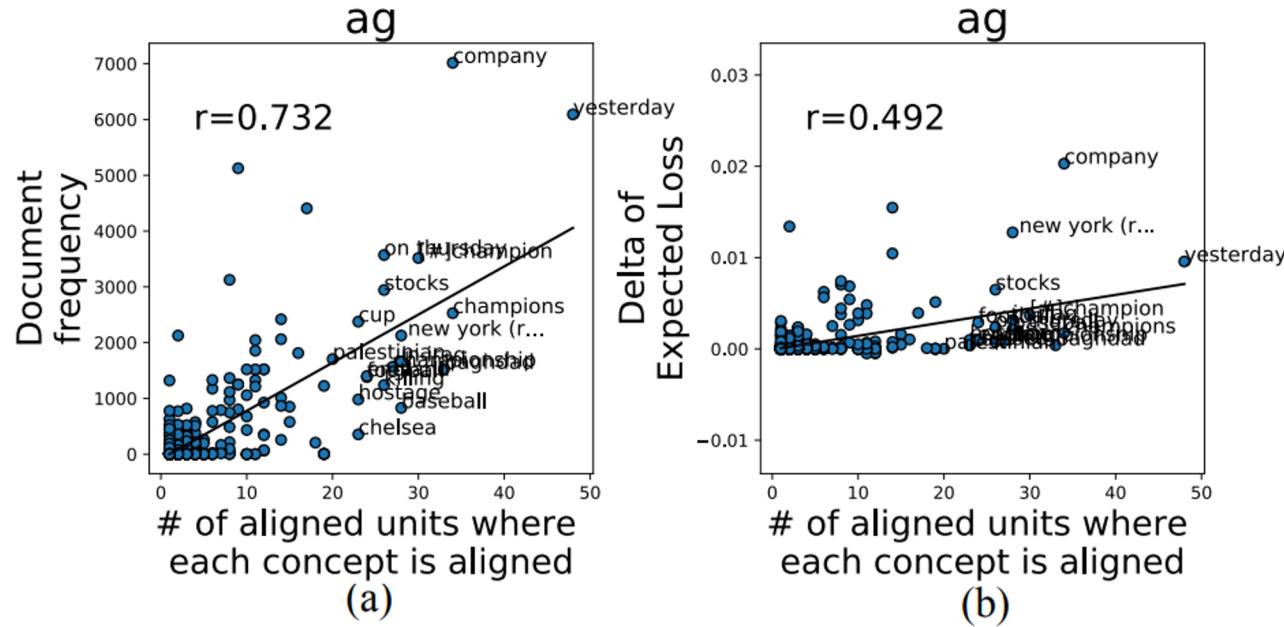


Figure 7: Correlations between the number of units per concept and (a) document frequency and (b) delta of expected loss. Pearson correlation coefficients are measured at the final layer of the AG News sentence classification task. Some concepts aligned to many units are annotated. Results on other tasks are available in Appendix F.

Conclusion and Future Work:

- Proposed a simple but highly effective concept alignment method for character-level CNNs to confirm that each unit of the hidden layers serves as detectors of natural language concepts.
- Consequently, authors shed light on how deep representations capture the natural language, and how they vary with various conditions.
- An interesting future direction is to extend the concept coverage from natural language to more abstract forms such as sentence structure, nuance, and tone.
- Combining definition of concepts with the attention mechanism.

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