Compositional Explanations of Neurons

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Abstract

We describe a procedure for explaining neurons in deep representations by identifying *compositional* logical concepts that closely approximate neuron behavior. Compared to prior work that uses atomic labels as explanations, analyzing neurons compositionally allows us to more precisely and expressively characterize their behavior. We use this procedure to answer several questions on interpretability in models for vision and natural language processing. First, we examine the kinds of abstractions learned by neurons. In image classification, we find that many neurons learn highly abstract but semantically coherent visual concepts, while other *polysemantic* neurons detect multiple unrelated features; in natural language inference (NLI), neurons learn shallow lexical heuristics from dataset biases. Second, we see whether compositional explanations give us insight into model performance: vision neurons that detect human-interpretable concepts are positively correlated with task performance, while NLI neurons that fire for shallow heuristics are negatively correlated with task performance. Finally, we show how compositional explanations provide an accessible way for end users to produce simple "copy-paste" adversarial examples that change model behavior in predictable ways.

1 Introduction

In this paper, we describe a procedure for automatically explaining logical and perceptual abstractions encoded by individual neurons in deep networks. Prior work in neural network interpretability has found that neurons in models trained for a variety of tasks learn human-interpretable concepts, e.g. faces or parts-of-speech, often without explicit supervision [5, 10, 11, 27]. Yet many existing interpretability methods are limited to ad-hoc explanations based on manual inspection of model visualizations or inputs [10, 26, 27, 35, 38, 39]. To instead automate explanation generation, recent work [5, 11] has proposed to use labeled "probing datasets" to explain neurons by identifying concepts (e.g. *dog* or *verb*) closely aligned with neuron behavior.

However, the atomic concepts available in probing datasets may be overly simplistic explanations of neurons. A neuron might robustly respond to images of dogs without being exclusively specialized for dog detection; indeed, some have noted the presence of *polysemantic* neurons in vision models that detect multiple concepts [12, 27]. The extent to which these neurons have learned meaningful perceptual abstractions (versus detecting unrelated concepts) remains an open question. More generally, neurons may be more accurately characterized not just as simple detectors, but rather as operationalizing complex decision rules composed of multiple concepts (e.g. *dog faces, cat bodies, and car windows*). Existing tools are unable to surface such compositional concepts automatically.

We propose to generate explanations by searching for logical forms defined by a set of composition operators over primitive concepts (Figure 1). Compared to previous work [5], these explanations serve as better approximations of neuron behavior, and identify behaviors that help us answer a variety of interpretability questions across vision and natural language processing (NLP) models. First, what kind of logical concepts are learned by deep models in vision and NLP? Second, do the

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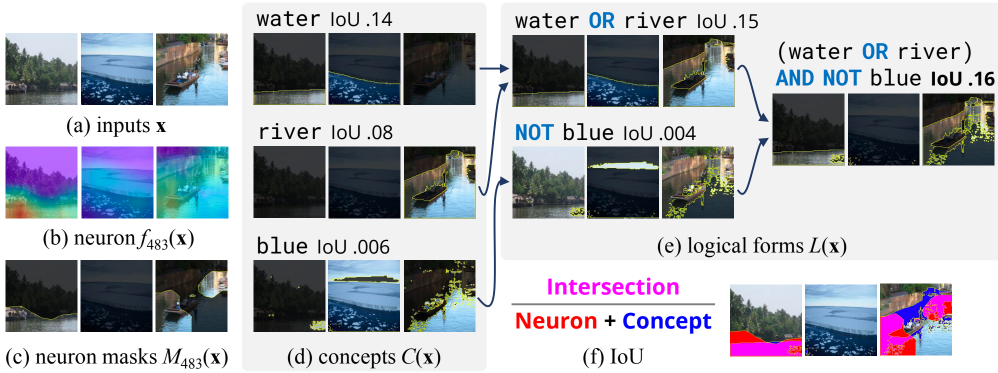

Figure 1: Given a set of inputs (a) and scalar neuron activations (b) converted into binary masks (c), we generate an explanation via beam search, starting with an inventory of primitive concepts (d), then incrementally building up more complex logical forms (e). We attempt to maximize the IoU score of an explanation (f); depicted is the IoU of $M_{483}(\mathbf{x})$ and `(water OR river) AND NOT blue`.

quality and interpretability of these learned concepts relate to model performance? Third, can we use the logical concepts encoded by neurons to control model behavior in predictable ways? We find that:

1. Neurons learn compositional concepts: in **image classification**, we identify neurons that learn meaningful perceptual abstractions (e.g. *tall structures*) and others that fire for unrelated concepts. In natural language inference (**NLI**), we show that shallow heuristics (based on e.g. gender and lexical overlap) are not only learned, but reified in individual neurons.
2. Compositional explanations help predict model accuracy, but interpretability is not always associated with accurate classification: in **image classification**, human-interpretable abstractions are *correlated* with model performance, but in **NLI**, neurons that reflect shallower heuristics are *anticorrelated* with performance.
3. Compositional explanations allow users to predictably manipulate model behavior: we can generate crude "copy-paste" adversarial examples based on inserting words and image patches to target individual neurons, in contrast to black-box approaches [1, 36, 37].

2 Generating compositional explanations

Consider a neural network model f that maps inputs $\mathbf{x}$ to vector representations $r \in \mathbb{R}^d$. f might be a prefix of a convolutional network trained for image classification or a sentence embedding model trained for a language processing task. Now consider an individual neuron $f_n(\mathbf{x}) \in \mathbb{R}$ and its activation on a set of concrete inputs (e.g. ResNet-18 [15] layer 4 unit 483; Figure 1a–b). How might we explain this neuron's behavior in human-understandable terms?

The intuition underlying our approach is shared with the NetDissect procedure of Bau et al. [5]; here we describe a generalized version. The core of this intuition is that a good explanation is a *description* (e.g. a named category or property) that identifies the same inputs for which f_n activates. Formally, assume we have a space of pre-defined atomic *concepts* $C \in \mathcal{C}$ where each concept is a function $C : \mathbf{x} \mapsto \{0, 1\}$ indicating whether $\mathbf{x}$ is an instance of C. For image pixels, concepts are image segmentation masks; for the *water* concept, $C(\mathbf{x})$ is 1 when $\mathbf{x}$ is an image region containing water (Figure 1d). Given some measure δ of the similarity between neuron activations and concepts, NetDissect explains the neuron f_n by searching for the concept C that is most similar:

$$\textsc{Explain-NetDissect}(n) = \arg\max_{C \in \mathcal{C}} \delta(n, C). \tag{1}$$

While δ can be arbitrary, Bau et al. [5] first *threshold* the continuous neuron activations $f_n(\mathbf{x})$ into binary masks $M_n(\mathbf{x}) \in \{0, 1\}$ (Figure 1c). This can be done *a priori* (e.g. for post-ReLU activations, thresholding above 0), or by dynamically thresholding above a neuron-specific percentile. We can then compare binary neuron masks and concepts with the Intersection over Union score (IoU, or Jaccard similarity; Figure 1f):

$$\delta(n, C) \triangleq \text{IoU}(n, C) = \Big[\sum_{\mathbf{x}} \mathbb{1}(M_n(\mathbf{x}) \wedge C(\mathbf{x}))\Big] \,/\, \Big[\sum_{\mathbf{x}} \mathbb{1}(M_n(\mathbf{x}) \vee C(\mathbf{x}))\Big]. \tag{2}$$

Compositional search. The procedure described in Equation 1 can only produce explanations from the fixed, pre-defined concept inventory $\mathcal{C}$. Our main contribution is to combinatorially expand the set of possible explanations to include *logical forms* $\mathcal{L}(\mathcal{C})$ defined inductively over $\mathcal{C}$ via composition operations such as disjunction (OR), conjunction (AND), and negation (NOT), e.g. $(L_1 \text{ AND } L_2)(\mathbf{x}) = L_1(\mathbf{x}) \wedge L_2(\mathbf{x})$ (Figure 1e). Formally, if Ω_η is the set of η-ary composition functions, define $\mathcal{L}(\mathcal{C})$:

1. Every primitive concept is a logical form: $\forall C \in \mathcal{C}$, we have $C \in \mathcal{L}(\mathcal{C})$.
2. Any composition of logical forms is a logical form: $\forall \eta,\ \omega \in \Omega_\eta,\ (L_1, \dots, L_\eta) \in \mathcal{L}(\mathcal{C})^\eta$, where $\mathcal{L}(\mathcal{C})^\eta$ is the set of η-tuples of logical forms in $\mathcal{L}(\mathcal{C})$, we have $\omega(L_1, \dots, L_\eta) \in \mathcal{L}(\mathcal{C})$.

Now we search for the best logical form $L \in \mathcal{L}(\mathcal{C})$:

$$\text{EXPLAIN-COMP}(n) = \arg\max_{L \in \mathcal{L}(\mathcal{C})} \text{IoU}(n, L). \tag{3}$$

The $\arg\max$ in Equation 3 ranges over a structured space of compositional expressions, and has the form of an inductive program synthesis problem [23]. Since we cannot exhaustively search $\mathcal{L}(\mathcal{C})$, in practice we limit ourselves to formulas of maximum length N, by iteratively constructing formulas from primitives via beam search with beam size $B = 10$. At each step of beam search, we take the formulas already present in our beam, compose them with new primitives, measure IoU of these new formulas, and keep the top B new formulas by IoU, as shown in Figure 1e.

3 Tasks

The procedure we have described above is model- and task-agnostic. We apply it to two tasks in vision and NLP: first, we investigate a scene recognition task explored by the original NetDissect work [5], which allows us to examine compositionality in a task where neuron behavior is known to be reasonably well-characterized by atomic labels. Second, we examine *natural language inference* (NLI): an example of a seemingly challenging NLP task which has recently come under scrutiny due to models' reliance on shallow heuristics and dataset biases [13, 14, 22, 25, 30, 37]. We aim to see whether compositional explanations can uncover such undesirable behaviors in NLI models.

Image Classification. NetDissect [5] examines whether a convolutional neural network trained on a scene recognition task has learned detectors that correspond to meaningful abstractions of objects. We take the final 512-unit convolutional layer of a ResNet-18 [15] trained on the Places365 dataset [40], probing for concepts in the ADE20k scenes dataset [41] with atomic concepts $\mathcal{C}$ defined by annotations in the Broden dataset [5]. There are 1105 unique concepts in ADE20k, categorized by Scene, Object, Part, and Color (see Figure 2 for examples).

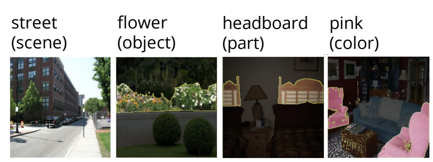

Figure 2: Example concepts from the Broden dataset [5], reproduced with permission.

Broden has pixel-level annotations, so for each input image $\mathbf{X} \in \mathbb{R}^{H \times W}$, inputs are indexed by pixels (i, j): $\mathbf{x}_{i,j} \in \mathcal{X}$. Let $f_n(\mathbf{x}_{i,j})$ be the activation of the nth neuron at position (i, j) of the image $\mathbf{X}$, after the neuron's activation map has been bilinearly upsampled from layer dimensions $H_l \times W_l$ to the segmentation mask dimensions $H \times W$. Following [5], we create neuron masks $M_n(x)$ via dynamic thresholding: let T_n be the threshold such that $P(f_n(\mathbf{x}) > T_n) = 0.005$ over all inputs $\mathbf{x} \in \mathcal{X}$. Then $M_n(\mathbf{x}) = \mathbb{1}(f_n(\mathbf{x}) > T_n)$. For composition, we use operations AND ($\wedge$), OR ($\vee$), and NOT ($\neg$), leaving more complex operations (e.g. relations like ABOVE and BELOW) for future work.

NLI. Given premise and hypothesis sentences, the task of NLI is to determine whether the premise *entails* the hypothesis, *contradicts* it, or neither (*neutral*). We investigate a BiLSTM baseline architecture proposed by [7]. A bidirectional RNN encodes both the premise and hypothesis to form 512-d representations. Both representations, and their elementwise product and difference, are then concatenated to form a 2048-d representation that is fed through a multilayer perceptron (MLP) with two 1024-d layers with ReLU nonlinearities and a final softmax layer. This model is trained on the Stanford Natural Language Inference (SNLI) corpus [6] which consists of 570K sentence pairs.

Neuron-level explanations of NLP models have traditionally analyzed how RNN hidden states detect word-level features as the model passes over the input sequence [4, 10], but in most NLI models, these

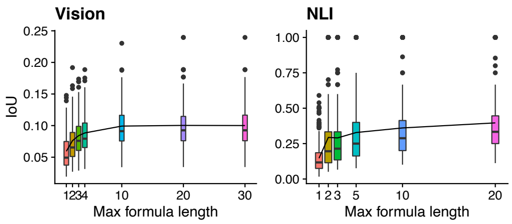

Figure 3: Distribution of IoU versus max formula length. The line indicates mean IoU. $N = 1$ is equivalent to NetDissect [5]; IoU scores steadily increase as max formula length increases.

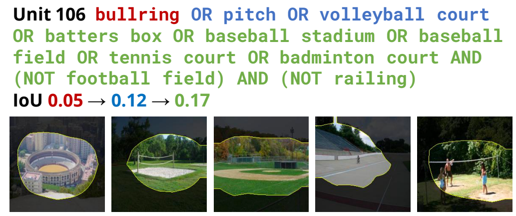

Figure 4: NetDissect [5] assigns unit 106 the label `bullring`, but in reality it is detects general sports fields, except football fields, as revealed by the **length 3** and **length 10** explanations.

RNN features are learned early and are often quite distant from the final sentence representation used for prediction. Instead, we analyze the MLP component, probing the 1024 neurons of the penultimate hidden layer for sentence-level explanations, so our inputs $\mathbf{x}$ are premise-hypothesis pairs.

We use the SNLI validation set as our probing dataset (10K examples). As our features, we take the Penn Treebank part of speech tags (labeled by SpaCy[1]) and the 2000 most common words appearing in the dataset. For each of these we create 2 concepts that indicate whether the word or part-of-speech appears in the premise or hypothesis. Additionally, to detect whether models are using lexical overlap heuristics [25], we define 4 concepts indicating that the premise and hypothesis have more than 0%, 25%, 50%, or 75% overlap, as measured by IoU between the unique words.

For our composition operators, we keep AND, OR, and NOT; in addition, to capture the idea that neurons might fire for groups of words with similar meanings, we introduce the unary NEIGHBORS operator. Given a word feature C, let the *neighborhood* $\mathcal{N}(C)$ be the set of 5 closest words C' to C, as measured by their cosine distance in GloVe embedding space [28]. Then, $\textsc{Neighbors}(C)(\mathbf{x}) = \bigvee_{C' \in \mathcal{N}(C)} C'(\mathbf{x})$ (i.e. the logical OR across all neighbors). Finally, since these are post-ReLU activations, instead of dynamically thresholding we simply define our neuron masks $M_n(\mathbf{x}) = \mathbb{1}(f_n(\mathbf{x}) > 0)$. There are many "dead" neurons in the model, and some neurons fire more often than others; we limit our analysis to neurons that activate reliably across the dataset, defined as being active at least 500 times (5%) across the 10K examples probed.

4 Do neurons learn compositional concepts?

Image Classification. Figure 3 (left) plots the distribution of IoU scores for the best concepts found for each neuron as we increase the maximum formula length N. When $N = 1$, we get EXPLAIN-NETDISSECT, with a mean IoU of 0.059; as N increases, IoU increases up to 0.099 at $N = 10$, a statistically significant 68% increase ($p = 2 \times 10^{-9}$). We see diminishing returns after length 10, so we conduct the rest of our analysis with length 10 logical forms. The increased explanation quality suggests that our compositional explanations indeed detect behavior beyond simple atomic labels: Figure 4 shows an example of a *bullring* detector which is actually revealed to detect fields in general.

We can now answer our first question from the introduction: are neurons learning meaningful abstractions, or firing for unrelated concepts? Both happen: we manually inspected a random sample of 128 neurons in the network and their length 10 explanations, and found that **69%** learned some meaningful combination of concepts, while **31%** were *polysemantic*, firing for at least some unrelated concepts. The 88 "meaningful" neurons fell into 3 categories (examples in Figure 5; more in Appendix A):

1. 50 (57%) learn a perceptual **abstraction** that is also lexically coherent, in that the primitive words in the explanation are semantically related (e.g. to *towers* or *bathrooms*; Figure 5a).
2. 28 (32%) learn a perceptual **abstraction** that is *not* lexically coherent, as the primitives are not obviously semantically related. For example, `cradle OR autobus OR fire escape` is a vertical rails detector, but we have no annotations of vertical rails in Broden (Figure 5b).
3. 10 (12%) have the form L_1 `AND NOT` L_2, which we call **specialization**. They detect more specific variants of Broden concepts (e.g. `(water OR river) AND NOT blue`; Figure 5c).

[1] `https://spacy.io/`

Figure 5: Image classification explanations categorized by **semantically coherent** abstraction (a–b) and specialization (c), and **unrelated** polysemanticity (d). For clarity, logical forms are length $N = 3$.

Unit 870 (gender-sensitive)

`((((NOT hyp:man) AND pre:man) OR hyp:eating) AND (NOT pre:woman)) OR hyp:dancing`

IoU **0.123** w_{entail} -0.046 w_{neutral} -0.021 w_{contra} 0.040

Pre A guy pointing at a giant blackberry.
Hyp A woman tearing down a giant display.
Act **29.31** True **contra** Pred **contra**

Pre A man in a hat is working with...flowers.
Hyp Women are working with flowers.
Act **27.64** True **contra** Pred **contra**

Unit 15 (sitting only in hypothesis)

`hyp:eating OR hyp:sitting OR hyp:sleeping OR hyp:sits AND (NOT pre:sits)`

IoU **0.239** w_{entail} -0.083 w_{neutral} -0.059 w_{contra} 0.086

Pre A person...is walking through an airport.
Hyp A woman sits in the lobby waiting on the doctor.
Act **30.68** True **contra** Pred **contra**

Pre A man jumps over another man...
Hyp Two men are sitting down, watching the game.
Act **27.64** True **contra** Pred **contra**

Unit 99 (high overlap)

`((NOT hyp:JJ) AND overlap-75% AND (NOT pre:people)) OR pre:basket OR pre:tv`

IoU **0.118** w_{entail} 0.043 w_{neutral} -0.029 w_{contra} -0.021

Pre A woman in a light blue jacket is riding a bike.
Hyp A women in a jacket riding a bike.
Act **19.13** True **entail** Pred **entail**

Pre A girl in a pumpkin dress sitting at a table.
Hyp There is a girl in a pumpkin dress sitting at a table.
Act **17.84** True **entail** Pred **entail**

Unit 473 (unclear)

`((NOT hyp:sleeping) AND (pre:NN OR pre:NNS)) AND (NOT hyp:alone) AND (NOT hyp:nobody)`

IoU **0.586** w_{entail} 0.020 w_{neutral} 0.016 w_{contra} -0.050

Pre A gentleman in a striped shirt gesturing with a stick...
Hyp A gentleman in a striped shirt joyously gesturing.
Act **31.62** True **neutral** Pred **neutral**

Pre An Asian man in a...uniform diving...in a game.
Hyp A person in a uniform does something.
Act **29.76** True **neutral** Pred **entail**

Figure 6: NLI length 5 explanations. For each neuron, we show the explanation (e.g. `pre:x` indicates x appears in the premise), IoU, class weights $w_{\{\text{entail,neutral,contra}\}}$, and activations for 2 examples.

The observation that IoU scores do not increase substantially past length 10 corroborates the finding of [12], who also note that few neurons detect more than 10 unique concepts in a model. Our procedure, however, allows us to more precisely characterize whether these neurons detect abstractions or unrelated disjunctions of concepts, and identify more interesting cases of behavior (e.g. *specialization*). While composition of Broden annotations explains a majority of the abstractions learned, there is still considerable unexplained behavior. The remaining behavior could be due to noisy activations, neuron misclassifications, or detection of concepts absent from Broden.

NLI. NLI IoU scores reveal a similar trend (Figure 3, right): as we increase the maximum formula length, we account for more behavior, though scores continue increasing past length 30. However, short explanations are already useful: Figure 6, Figure 9 (explained later), and Appendix B show example length 5 explanations. Many neurons correspond to simple decision rules based mostly on lexical features: for example, several neurons are *gender sensitive* (Unit 870), and activate for *contradiction* when the premise, but not the hypothesis, contains the word `man`. Others fire for verbs that are often associated with a specific label, such as `sitting`, `eating`, or `sleeping`. Many of these words have high *pointwise mutual information* (PMI) with the class prediction; as noted by [14], the top two highest words by PMI with *contradiction* are `sleeping` (15) and `nobody` (39, Figure 9). Still others (99) fire when there is high lexical overlap between premise and hypothesis, another heuristic noted in the literature [25]. Finally, there are neurons that are not well explained by this feature set (473). In general, we have found evidence that many neurons correspond to the kinds of simple heuristics [14, 25] that make NLI models brittle to out-of-distribution data [13, 22, 37]. Here, we demonstrate these heuristics are actually reified as individual features in deep representations.

5 Do interpretable neurons contribute to model accuracy?

A natural question to ask is whether it is empirically desirable to have more (or less) interpretable neurons, with respect to the kinds of concepts identified above. To answer this, we measure the performance of the entire model on the task of interest when the neuron is activated. In other words, for neuron n, what is the model accuracy on predictions for inputs where $M_n(\mathbf{x}) = 1$? In **image classification**, we find that the more interpretable the neuron (by IoU), the more accurate the model is when the neuron is active (Figure 7, left; $r = 0.31$, $p < 1e-13$); the correlation increases as the formula length increases and we are better able to explain neuron behavior. Given that we are measuring abstractions over the human-annotated features deemed relevant for scene classification, this suggests, perhaps unsurprisingly, that neurons that detect more interpretable concepts are more accurate.

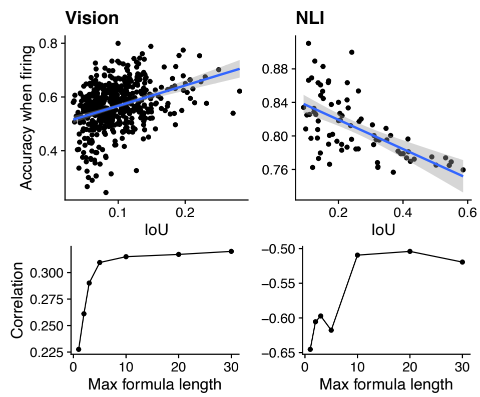

Figure 7: Top: neuron IoU versus model accuracy over inputs where the neuron is active for vision (length 10) and NLI (length 3). Bottom: Pearson correlation between these quantities versus max formula length.

However, when we apply the same analysis to the **NLI** model, the *opposite* trend occurs: neurons that we are better able to explain are *less* accurate (Figure 7, right; $r = -0.60$, $p < 1e-08$). Unlike vision, most sentence-level logical descriptions recoverable by our approach are spurious by definition, as they are too simple compared to the true reasoning required for NLI. If a neuron can be accurately summarized by simple deterministic rules, this suggests the neuron is making decisions based on spurious correlations, which is reflected by the lower performance. Analogously, the more *restricted* our feature set (by maximum formula length), the better we capture this anticorrelation. One important takeaway is that the "interpretability" of these explanations is not *a priori* correlated with performance, but rather dependent on the concepts we are searching for: given the right concept space, our method can identify behaviors that may be correlated *or* anticorrelated with task performance.

6 Can we target explanations to change model behavior?

Finally, we see whether compositional explanations allow us to manipulate model behavior. In both models, we have probed the final hidden representation before a final softmax layer produces the class predictions. Thus, we can measure a neuron's contribution to a specific class with the weight between the neuron and the class, and see whether constructing examples that activate (or inhibit) these neurons leads to corresponding changes in predictions. We call these "copy-paste" adversarial examples to differentiate them from standard adversarial examples involving imperceptible perturbations [36].

Image Classification. Figure 8 shows some Places365 classes along with the neurons that most contribute to the class as measured by the connection weight. In many cases, these connections are

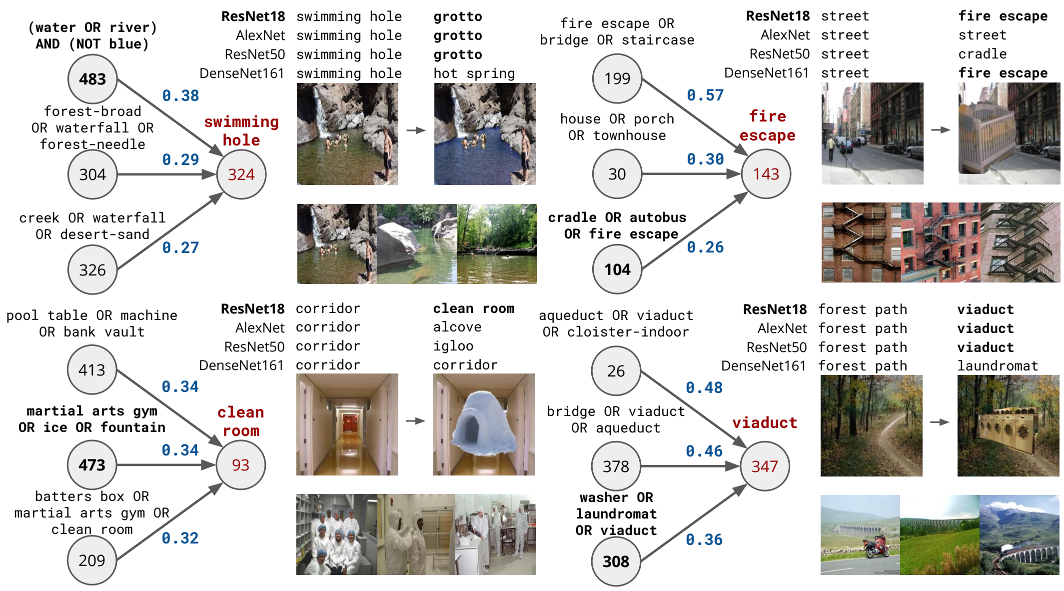

Figure 8: "copy-paste" adversarial examples for vision. For each **scene**, the units that contribute most (by **connection weight**) are shown, along with their explanations. We target the **bold** explanations to crudely modify an input image and change the prediction towards/away from the scene.

Unit 39 (nobody in hypothesis)

`hyp:nobody AND (NOT pre:hair) AND (NOT pre:RB) AND (NOT pre:'s)`

IoU **0.465** w_{entail} -0.117 $w_{neutral}$ -0.053 w_{contra} 0.047

Pre Three women prepare a meal in a kitchen.
Orig Hyp The ladies are cooking.
Adv Hyp ***Nobody but*** the ladies are cooking.
True **entail** $\xrightarrow{adv}$ **neutral** Pred **entail** $\xrightarrow{adv}$ **contra**

Unit 133 (couch words in hypothesis)

`NEIGHBORS(hyp:couch) OR hyp:inside OR hyp:home OR hyp:indoors OR hype:eating`

IoU **0.202** w_{entail} -0.125 $w_{neutral}$ -0.024 w_{contra} 0.088

Pre 5 women sit around a table doing some crafts.
Orig Hyp 5 women sit around a table.
Adv Hyp 5 women sit around a table ***near a couch***.
True **entail** $\xrightarrow{adv}$ **neutral** Pred **entail** $\xrightarrow{adv}$ **contra**

Unit 15 (sitting only in hypothesis)

`hyp:eating OR hyp:sitting OR hyp:sleeping OR hyp:sits AND (NOT pre:sits)`

IoU **0.239** w_{entail} -0.083 $w_{neutral}$ -0.059 w_{contra} 0.086

Orig Pre A blond woman is holding 2 golf balls while reaching down into a golf hole.
Adv Pre A blond woman is holding 2 golf balls.
Hyp A blond woman is sitting down.
True **contra** $\xrightarrow{adv}$ **neutral** Pred **contra** $\xrightarrow{adv}$ **contra**

Unit 941 (inside/indoors in hypothesis)

`hyp:inside OR hyp:not OR hyp:indoors OR hyp:moving OR hyp:something`

IoU **0.151** w_{entail} 0.086 $w_{neutral}$ -0.030 w_{contra} -0.023

Orig Pre Two people are sitting in a station.
Adv Pre Two people are sitting in a ***pool***.
Hyp A couple of people are inside and not standing.
True **entail** $\xrightarrow{adv}$ **neutral** Pred **entail** $\xrightarrow{adv}$ **entail**

Figure 9: "copy-paste" adversarial examples for NLI. Taking an example from SNLI, we construct an **adversarial (adv)** premise or hypothesis which changes the true label and results in an *incorrect* model prediction (original label/prediction $\xrightarrow{adv}$ adversarial label/prediction).

sensible; water, foliage, and rivers contribute to a *swimming hole* prediction; houses, staircases, and fire escape (objects) contribute to *fire escape* (scene). However, the explanations in **bold** involve polysemanticity or spurious correlations. In these cases, we found it is possible to construct a "copy-paste" example which uses the neuron explanation to predictably alter the prediction. In some cases, these adversarial examples are generalizable across networks besides the probed ResNet-18, causing the same behavior across AlexNet [24], ResNet-50 [15], and DenseNet-161 [21], all trained on Places365. For example, one major contributor to the *swimming hole* scene (top-left) is a neuron that fires for non-blue water; making the water blue switches the prediction to *grotto* in many models. The consistency of this misclassification suggests that models are detecting underlying biases in the training data. Other examples include a neuron contributing to *clean room* that also detects ice and igloos; putting an igloo in a corridor causes a prediction to shift from *corridor* to *clean room*, though this does not occur across models, suggesting that this is an artifact specific to this model.

NLI. In NLI, we are able to trigger similar behavior by targeting spurious neurons (Figure 9): a neuron that detects the presence of `nobody` in the hypothesis predicts *contradiction* for nearly all such inputs; another neuron similarly predicts *contradiction* when `couch` appears in the hypothesis.

Overall, these examples are reminiscent of the image-patch attacks of [9], adversarial NLI inputs [1, 37], and the data collection process for recent *counterfactual* NLI datasets [13, 22], but instead of searching among neuron visualizations or using black-box optimization to synthesize examples, we use explanations as a transparent guide for crafting perturbations by hand.

7 Related Work

Interpretability. Interpretability in deep neural networks has received considerable attention over the past few years. Our work extends existing work on generating explanations for individual neurons in deep representations [4, 5, 10–12, 27], in contrast to analysis or probing methods that operate at the level of entire representations (e.g. [2, 19, 29]). Neuron-level explanations are fundamentally limited, since they cannot detect concepts distributed across multiple neurons, but this has advantages: first, neuron-aligned concepts offer evidence for representations that are *disentangled* with respect to concepts of interest; second, they inspect unmodified "surface-level" neuron behavior, avoiding recent debates on how complex representation-level probing methods should be [18, 29].

Complex explanations. In generating logical explanations of model behavior, one related work is the Anchors procedure of [33], which finds conjunctions of features that "anchor" a model's prediction in some local neighborhood in input space. Unlike Anchors, we do not explain local model behavior, but rather globally consistent behavior of neurons across an entire dataset. Additionally, we use not just conjunctions, but more complex compositions tailored to the domain of interest.

As our compositional formulas increase in complexity, they begin to resemble approaches to generating *natural language* explanations of model decisions [2, 8, 16, 17, 31]. These methods primarily operate at the representation level, or describe rationales for individual model predictions. One advantage of our logical explanations is that they are directly grounded in features of the data and have explicit measures of quality (i.e. IoU), in contrast to language explanations generated from black-box models that are often themselves uninterpretable: for example, [17] note that naive language explanation methods often mention evidence not directly present in the input.

Dataset biases and adversarial examples. Complex neural models are often *brittle*: they fail to generalize to out-of-domain data [3, 13, 22, 32] and are susceptible to adversarial attacks where inputs are subtly modified in a way that causes a model to fail catastrophically [34, 36, 37]. This may be due in part to biases in dataset collection [3, 14, 30, 32], and models fail on datasets which eliminate these biases [3, 13, 22, 32]. In this work we suggest that these artifacts are learned to the degree that we can identify specific detectors for spurious features in representation space, enabling "copy-paste" adversarial examples constructed solely based on the explanations of individual neurons.

8 Discussion

We have described a procedure for obtaining compositional explanations of neurons in deep representations. These explanations more precisely characterize the behavior learned by neurons, as shown through higher measures of explanation quality (i.e. IoU) and qualitative examples of models learning perceptual abstractions in vision and spurious correlations in NLI. Specifically, these explanations (1) identify abstractions, polysemanticity, and spurious correlations localized to specific units in the representation space of deep models; (2) can disambiguate higher versus lower quality neurons in a model with respect to downstream performance; and (3) can be targeted to create "copy-paste" adversarial examples that predictably modify model behavior.

Several unanswered questions emerge: (1) does *model pruning* [20] more selectively remove the "lower quality" neurons identified by this work? (2) Can we distill a deep model into a simple classifier over binary concept detectors defined by our neuron explanations? (3) Can we use neuron interpretability as a regularization signal during training, and does encouraging neurons to learn more interpretable abstractions result in better downstream task performance?

Broader Impact

Tools for model introspection and interpretation are crucial for better understanding the behavior of black-box models, especially as they make increasingly important decisions in high-stakes societal applications. We believe that the explanations generated in this paper can help unveil richer concepts that represent spurious correlations and potentially problematic biases in models, thus helping practitioners better understand the decisions made by machine learning models.

Nonetheless, we see two limitations with this method as it stands: (1) it currently requires technical expertise to implement, limiting usability by non-experts; (2) it relies on annotated datasets which may be expensive to collect, and may be biased in the kinds of features they contain (or omit). If a potential feature of interest is not present in the annotated dataset, it cannot appear in an explanation. Both of these issues can be ameliorated with future work in (1) building easier user interfaces for explainability, and (2) reducing data annotation requirements.

In high stakes cases, e.g. identifying model biases, care should also be taken to avoid relying too heavily on these explanations as causal proof that a model is encoding a concept, or assuming that the absence of an explanation is proof that the model does not encode the concept (or bias). We provide evidence that neurons exhibit surface-level behavior that is well-correlated with human-interpretable concepts, but by themselves, neuron-level explanations cannot identify the full array of concepts encoded in representations, nor establish definitive causal chains between inputs and decisions.

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A Additional image classification examples

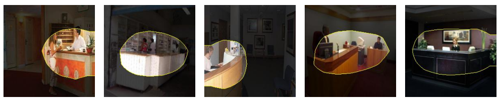
Examples are not cherry picked; we enumerate neurons 0–39.

Unit 0 (lexical and perceptual: bars/surfaces)

Length 1 **IoU** 0.075 `reception`

Length 3 **IoU** 0.106 `((reception OR work surface) OR bar)`

Length 10 **IoU** 0.107 `((((((((reception OR work surface) OR bar) OR ticket counter) OR button panel) AND (NOT desk)) AND (NOT table)) AND (NOT home office)) AND (NOT bottle)) AND (NOT drawer))`



Unit 1 (lexical and perceptual: windows/shelves)

Length 1 **IoU** 0.045 `shop window`

Length 3 **IoU** 0.084 `((shop window OR pantry) OR liquor store outdoor)`

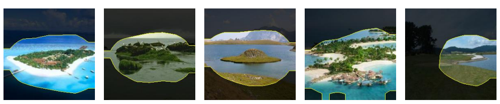
Length 10 **IoU** 0.103 `((((((((shop window OR pantry) OR liquor store outdoor) OR shopfront) OR toyshop) OR gift shop) OR convenience store outdoor) OR pub outdoor) OR trade name) OR shoe shop)`

Unit 2 (lexical and perceptual: islands/grass/water)

Length 1 **IoU** 0.063 `sea`

Length 3 **IoU** 0.078 `((sea OR marsh) OR lake)`

Length 10 **IoU** 0.090 `((((((((sea OR marsh) OR lake) OR island) AND (NOT ocean)) OR bayou) OR golf course) AND (NOT tree)) OR bog) OR watering hole)`

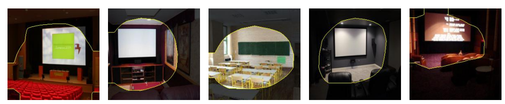


Unit 3 (lexical and perceptual: screens)

Length 1 **IoU** 0.094 `auditorium`

Length 3 **IoU** 0.177 `((auditorium OR movie theater indoor) OR theater indoor procenium)`

Length 10 **IoU** 0.230 `((((((((auditorium OR movie theater indoor) OR theater indoor procenium) OR silver screen) OR conference center) AND (NOT ceiling)) OR blackboard) AND (NOT floor)) OR lecture room) AND (NOT ceiling))`

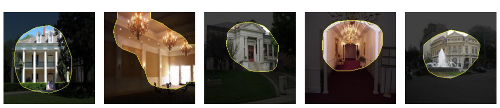


Unit 4 (polysemantic: columns/chandeliers)

Length 1 **IoU** 0.025 `courthouse`

Length 3 **IoU** 0.049 `((courthouse OR throne room) OR ballroom)`

Length 10 **IoU** 0.064 `((((((((courthouse OR throne room) OR chandelier) OR column) OR ballroom) OR bandstand) OR embassy) AND (NOT living room)) AND (NOT poolroom home)) AND (NOT courtroom))`

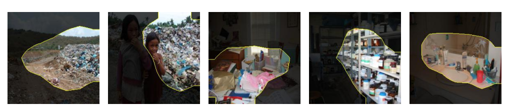


Unit 5 (perceptual only: debris)

Length 1 **IoU** 0.033 `shelf`

Length 3 **IoU** 0.062 `((slum OR toilet) OR pantry)`

Length 10 **IoU** 0.074 `((((((((slum OR toilet) OR pantry) OR rubbish) OR bazaar outdoor) OR bucket) OR washer) OR plaything) OR workshop) AND (NOT market outdoor))`

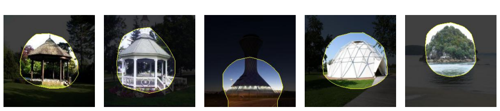


Unit 6 (lexical and perceptual: domes)

Length 1 **IoU** 0.049 `gazebo exterior`

Length 3 **IoU** 0.073 `((gazebo exterior OR tent) OR dome)`

Length 10 **IoU** 0.098 `((((((((gazebo exterior OR tent) OR dome) OR big top) OR hut) OR island) OR butte) OR mausoleum) OR greenhouse) OR bandstand)`

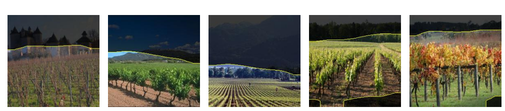


Unit 7 (lexical and perceptual: fields of plants)

Length 1 **IoU** 0.057 `vineyard`

Length 3 **IoU** 0.127 `((vineyard OR orchard) OR corn field)`

Length 10 **IoU** 0.133 `((((vineyard OR orchard) OR corn field) OR vineyard) AND (NOT hedge))`



Unit 8 (lexical and perceptual: plants)

Length 1 **IoU** 0.098 `greenhouse indoor`

Length 3 **IoU** 0.130 `((greenhouse indoor OR greenhouse) OR vegetable garden)`

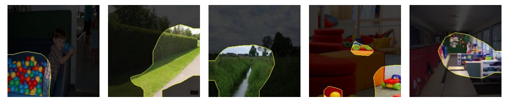
Length 10 **IoU** 0.156 `((((((((greenhouse indoor OR greenhouse) OR vegetable garden) OR vineyard) OR leaves) OR florist shop indoor) OR corn field) OR leaf) AND (NOT field)) OR vegetable garden)`

Unit 9 (polysemantic: grass/balls/other)

Length 1 **IoU** 0.037 `grass`

Length 3 **IoU** 0.050 `((ball pit OR plaything) OR kindergarden classroom)`

Length 10 **IoU** 0.053 `((((((((ball pit OR plaything) OR kindergarden classroom) OR fruit) OR day care center) OR lake artificial) AND (NOT water)) AND (NOT painting)) AND (NOT pedestal)) AND (NOT fence))`

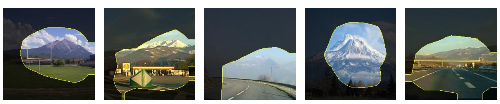


Unit 10 (polysemantic: mountains/highway)

Length 1 **IoU** 0.065 `highway`

Length 3 **IoU** 0.088 `((highway OR field cultivated) AND (NOT sky))`

Length 10 **IoU** 0.092 `((((((((highway OR field cultivated) AND (NOT sky)) OR wheat field) OR desertand) AND (NOT sky)) OR field road) AND (NOT sky)) OR mountain road) AND (NOT earth))`



Unit 11 (polysemantic: people/others)

Length 1 **IoU** 0.072 `person`

Length 3 **IoU** 0.077 `((person OR booth indoor) AND (NOT art studio))`

Length 10 **IoU** 0.078 `((((((((person AND (NOT pink)) OR booth indoor) AND (NOT art studio)) AND (NOT head)) OR market indoor) OR booth indoor) OR torso) AND (NOT conference center)) AND (NOT fire station))`

Unit 12 (polysemantic: dining rooms/fire escapes/others)

Length 1 **IoU** 0.042 `dining room`

Length 3 **IoU** 0.072 `((dining room AND table) OR fire escape)`

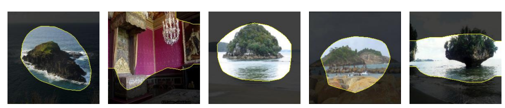
Length 10 **IoU** 0.085 `((((((((dining room AND table) OR fire escape) OR catacomb) OR shelter) OR throne room) OR altar) OR altarpiece) OR fire escape) AND (NOT chair))`

Unit 13 (polysemantic: islands/canopies/others)

Length 1 **IoU** 0.035 `islet`

Length 3 **IoU** 0.070 `((islet OR cavern indoor) OR canopy)`

Length 10 **IoU** 0.089 `((((((((islet OR cavern indoor) OR canopy) OR rope bridge) OR carousel) OR catacomb) OR bedchamber) OR altarpiece) OR niche) OR bayou)`



Unit 14 (perceptual only: fences/horizontal lines)

Length 1 **IoU** 0.038 `boxing ring`

Length 3 **IoU** 0.061 `((boxing ring OR corral) OR bleachers indoor)`

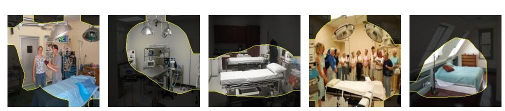
Length 10 **IoU** 0.081 `((((((((boxing ring OR corral) OR bleachers indoor) OR fence) OR military hut) OR wrestling ring indoor) OR bakery kitchen) OR barnyard) OR parking garage outdoor) OR horse)`

Unit 15 (perceptual only: beds)

Length 1 **IoU** 0.062 `operating room`

Length 3 **IoU** 0.104 `((operating room OR hospital room) OR cradle)`

Length 10 **IoU** 0.105 `((((((((operating room OR hospital room) OR cradle) OR dentists office) AND (NOT sink)) AND (NOT chest of drawers)) OR operating room) AND (NOT drawer)) AND (NOT footboard))`



Unit 16 (polysemantic: gyms/windmills/other)

Length 1 **IoU** 0.031 `ice skating rink indoor`

Length 3 **IoU** 0.064 `((ice skating rink indoor OR basketball court indoor) OR martial arts gym)`

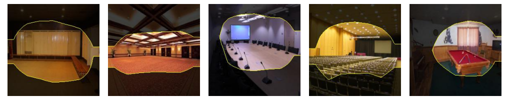
Length 10 **IoU** 0.112 `((((((((ice skating rink indoor OR basketball court indoor) OR martial arts gym) OR windmill) OR hangar indoor) OR boxing ring) OR wrestling ring indoor) OR fire escape) OR badminton court indoor) OR subway station corridor)`

Unit 17 (perceptual only: flat areas)

Length 1 **IoU** 0.068 `auditorium`

Length 3 **IoU** 0.101 `((auditorium OR conference center) OR movie theater indoor)`

Length 10 **IoU** 0.112 `((((((((auditorium OR conference center) OR movie theater indoor) OR theater indoor procenium) OR silver screen) OR courtroom) AND (NOT bench)) AND (NOT pedestal)) OR auditorium) AND (NOT swivel chair))`



Unit 18 (polysemantic: rocks/forests/other)

Length 1 **IoU** 0.047 `badlands`

Length 3 **IoU** 0.072 `((badlands OR forest needleleaf) OR slot machine)`

Length 10 **IoU** 0.081 `((((((((badlands OR forest needleleaf) OR slot machine) OR junkyard) OR arcade machine) OR cow) OR semidesert ground) OR animal) OR car interior backseat) AND (NOT green))`

Unit 19 (lexical and perceptual: cases)

Length 1 **IoU** 0.144 `bakeryhop`

Length 3 **IoU** 0.173 `((bakeryhop OR case) AND (NOT supermarket))`

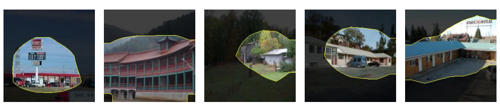
Length 10 **IoU** 0.188 `((((((((bakeryhop OR case) OR food) AND (NOT supermarket)) OR bakery kitchen) OR butchers shop) OR ice cream parlor) OR island) AND (NOT kitchen)) AND (NOT cabinet))`

Unit 20 (lexical and perceptual: houses/decks)

Length 1 **IoU** 0.036 `house`

Length 3 **IoU** 0.044 `((house OR motel) OR zen garden)`

Length 10 **IoU** 0.049 `((((((((house OR motel) OR zen garden) OR hunting lodge outdoor) OR lido deck outdoor) AND (NOT house)) OR student residence) OR swimming pool indoor) OR barnyard) AND (NOT barn))`



Unit 21 (polysemantic: bookcases/fire stations)

Length 1 **IoU** 0.063 `bookcase`

Length 3 **IoU** 0.098 `((bookcase OR fire station) OR book)`

Length 10 **IoU** 0.116 `((((((((bookcase OR fire station) OR book) OR videostore) OR garage door) OR library indoor) AND (NOT archive)) OR videos) OR convenience store indoor) OR exhibitor)`

Unit 22 (lexical and perceptual: bridges, possibly over water)

Length 1 **IoU** 0.035 `river`

Length 3 **IoU** 0.066 `((river OR bridge) OR rope bridge)`

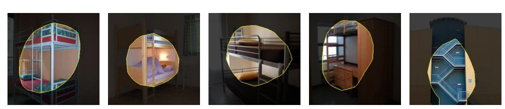
Length 10 **IoU** 0.080 `((((((((river OR bridge) OR rope bridge) OR creek) OR mountain path) OR aqueduct) OR gulch) OR sandbar) OR footbridge) AND (NOT canal natural))`

Unit 23 (perceptual only: vertical/perspective lines)

Length 1 **IoU** 0.046 `kitchen`

Length 3 **IoU** 0.058 `((youth hostel OR stove) OR galley)`

Length 10 **IoU** 0.070 `((((((((youth hostel OR stove) OR galley) OR microwave) OR work surface) OR telephone booth) OR cubicle office) OR kitchenette) OR exhaust hood) AND (NOT drawer))`



Unit 24 (polysemantic: beds/fireplaces/other)

Length 1 **IoU** 0.053 `fireplace`

Length 3 **IoU** 0.058 `((fireplace OR buffet) OR pulpit)`

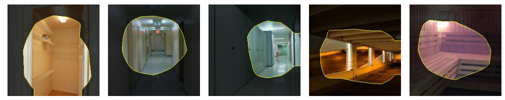
Length 10 **IoU** 0.060 `((((((((fireplace OR buffet) OR pulpit) OR microwave) AND (NOT poolroom home)) AND (NOT wet bar)) AND (NOT pane)) AND (NOT dinette home)) AND (NOT church indoor)) OR microwave)`

Unit 25 (perceptual only: empty corridors)

Length 1 **IoU** 0.067 `corridor`

Length 3 **IoU** 0.083 `((corridor OR sauna) OR elevator)`

Length 10 **IoU** 0.087 `((((((((corridor OR sauna) OR elevator) OR basement) OR fire escape) OR elevator door) OR cargo container interior) OR elevator freight elevator) AND (NOT door frame)) OR corridor)`



Unit 26 (lexical and perceptual: aqueducts)

Length 1 **IoU** 0.042 `aqueduct`

Length 3 **IoU** 0.079 `((aqueduct OR viaduct) OR cloister indoor)`

Length 10 **IoU** 0.097 `((((((((aqueduct OR viaduct) OR cloister indoor) OR bandstand) OR arch) OR aqueduct) OR viaduct) OR water tower) OR arcade) OR arcades)`

Unit 27 (perceptual only: dome-like things)

Length 1 **IoU** 0.032 `cockpit`

Length 3 **IoU** 0.054 `((cockpit OR wave) OR viaduct)`

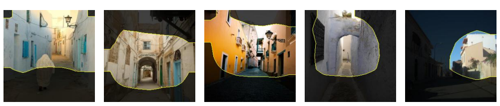
Length 10 **IoU** 0.066 `((((((((cockpit OR wave) OR viaduct) OR hovel) OR tent) OR dam) OR fountain) OR ice) OR dolmen) OR viaduct)`

Unit 28 (lexical and perceptual: mediterranean houses)

Length 1 **IoU** 0.045 `alley`

Length 3 **IoU** 0.081 `((medina OR kasbah) OR alley)`

Length 10 **IoU** 0.092 `(((((medina OR kasbah) OR alley) AND building) OR kasbah) OR medina) AND (NOT railing))`



Unit 29 (lexical and perceptual: house facades)

Length 1 **IoU** 0.088 `house`

Length 3 **IoU** 0.092 `((house OR porch) OR town house)`

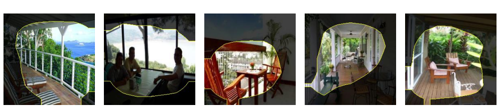
Length 10 **IoU** 0.093 `((((((((house AND (NOT building facade)) OR porch) OR town house) OR inn outdoor) AND (NOT plant)) AND (NOT alley)) AND (NOT dacha)) AND (NOT stairs)) AND (NOT general store outdoor))`

Unit 30 (lexical and perceptual: porches)

Length 1 **IoU** 0.075 `balcony interior`

Length 3 **IoU** 0.088 `((balcony interior OR dinette home) OR control tower indoor)`

Length 10 **IoU** 0.089 `(((((balcony interior OR dinette home) OR control tower indoor) AND (NOT door)) AND (NOT curtain)) AND (NOT armchair))`

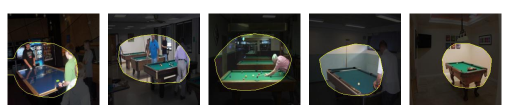


Unit 31 (polysemantic: pool tables/others)

Length 1 **IoU** 0.106 `pool table`

Length 3 **IoU** 0.124 `((pool table OR arcade machine) OR television camera)`

Length 10 **IoU** 0.126 `((((((pool table OR arcade machine) OR television camera) OR table tennis) AND (NOT television studio)) AND (NOT wet bar)) AND (NOT music studio))`



Unit 32 (perceptual only: red things)

Length 1 **IoU** 0.045 `red`

Length 3 **IoU** 0.058 `((fire station OR bullring) OR boxing ring)`

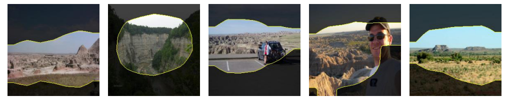
Length 10 **IoU** 0.069 `((((((((fire station OR bullring) OR boxing ring) OR throne room) OR telephone booth) OR big top) OR ring) OR joss house) OR autobus) AND (NOT grandstand))`

Unit 33 (lexical and perceptual: landscapes/horizons)

Length 1 **IoU** 0.078 `badlands`

Length 3 **IoU** 0.116 `((badlands OR desertand) OR oasis)`

Length 10 **IoU** 0.132 `((((((((badlands OR desertand) OR oasis) OR hoodoo) OR bulldozer) OR canyon) OR dam) AND (NOT rock)) OR badlands) AND (NOT tree))`

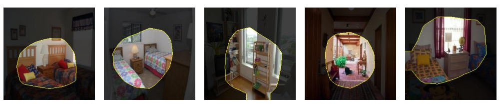


Unit 34 (polysemantic: beds and shelves)

Length 1 **IoU** 0.028 `bed`

Length 3 **IoU** 0.032 `((childs room OR dorm room) OR youth hostel)`

Length 10 **IoU** 0.034 `((((((((childs room OR dorm room) OR youth hostel) OR cushion) OR pantry) OR pillow) AND (NOT wardrobe)) AND (NOT door)) AND (NOT carpet)) AND (NOT attic))`



Unit 35 (polysemantic: water/other structures)

Length 1 **IoU** 0.019 `beach`

Length 3 **IoU** 0.029 `((beach OR tent) OR caravan)`

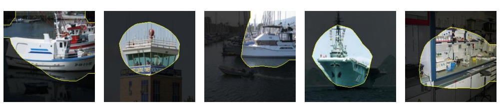
Length 10 **IoU** 0.039 `((((((((beach OR tent) OR caravan) OR hovel) OR bayou) OR manufactured home) OR watering hole) OR oasis) OR excavation) OR junkyard)`

Unit 36 (perceptual only: complex white structures)

Length 1 **IoU** 0.041 `boat`

Length 3 **IoU** 0.062 `((boat OR ship) OR aircraft carrier)`

Length 10 **IoU** 0.082 `((((((((boat OR ship) OR aircraft carrier) OR lighthouse) OR cannon) OR workshop) OR pier) OR roller coaster) OR water tower) OR dam)`

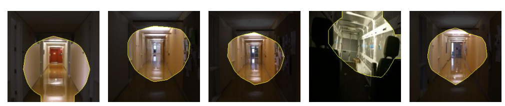


Unit 37 (perceptual only: empty halls/rooms)

Length 1 **IoU** 0.030 `corridor`

Length 3 **IoU** 0.049 `((airplane cabin OR subway interior) OR berth)`

Length 10 **IoU** 0.062 `((((((((airplane cabin OR subway interior) OR berth) OR operating room) OR hospital room) OR gymnasium indoor) OR swivel chair) AND (NOT conference room)) OR pilothouse indoor) AND (NOT desk))`

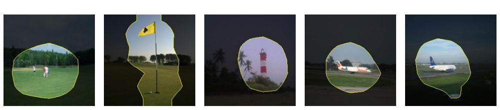


Unit 38 (perceptual only: things on grass)

Length 1 **IoU** 0.034 `lighthouse`

Length 3 **IoU** 0.060 `((lighthouse OR bullring) OR batters box)`

Length 10 **IoU** 0.076 `((((((((lighthouse OR bullring) OR batters box) OR fairway) OR water tower) OR plane) OR pitch) OR baseball field) AND (NOT sky)) OR lighthouse)`

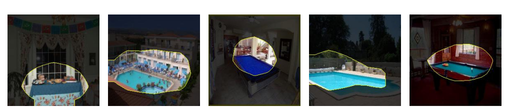


Unit 39 (perceptual only: flat surfaces)

Length 1 **IoU** 0.038 `bed`

Length 3 **IoU** 0.048 `((pool table OR pillow) OR swimming pool)`

Length 10 **IoU** 0.054 `((((((((pool table OR pillow) OR swimming pool) OR cushion) OR hotel outdoor) AND (NOT black)) AND (NOT swimming pool indoor)) OR eiderdown) AND (NOT black)) OR pillow)`



B Additional NLI examples

Examples are not cherry picked; we enumerate the first 25 neurons that fire reliably (i.e. at least 500 times across the validation dataset), skipping those already illustrated in the main paper.

Unit 0

`(((((NOT overlap-50%) AND pre:NN) AND (NOT hyp:VB)) AND (NOT hyp:outside)) AND (NOT hyp:near))`

IoU **0.355** w_{entail} -0.027 $w_{neutral}$ -0.018 w_{contra} 0.027

Pre a woman dressed in a blue long - sleeved shirt and wearing a hairnet .
Hyp the woman is naked and alone in the bathroom .
Act **43.58** True **contra** Pred **contra**

Pre two men are on a cherry picker proceeding to perform work at a construction site .
Hyp two men driving in a truck down an empty highway .
Act **42.50** True **contra** Pred **contra**

Pre these two poodles , one black and one brown , are playing .
Hyp the cats are brown and red .
Act **41.24** True **contra** Pred **contra**

Unit 6

`(((((NOT overlap-25%) AND pre:NN) AND (NOT hyp:people)) AND (NOT hyp:EX)) OR hyp:tall)`

IoU **0.239** w_{entail} -0.063 $w_{neutral}$ 0.022 w_{contra} 0.009

Pre a man in a blue helmet jumping off of a hill on a dirt bike .
Hyp the man is a professional athlete .
Act **26.31** True **neutral** Pred **neutral**

Pre a man standing in front of a class of asian students holding a picture of santa claus .
Hyp a tall human standing
Act **26.02** True **neutral** Pred **neutral**

Pre a girl prepares herself for the swim meet .
Hyp the girl has swam before .
Act **25.25** True **entail** Pred **neutral**

Unit 8

`((((hyp:for OR hyp:to) OR hyp:tall) OR hyp:their) AND (NOT hyp:next))`

IoU **0.247** w_{entail} -0.015 $w_{neutral}$ 0.023 w_{contra} 0.000

Pre a man is doing tricks on a skateboard .
Hyp a tall human doing tricks
Act **29.89** True **neutral** Pred **neutral**

Pre a guy on inline skates with a white hat is on a yellow rail .
Hyp the guy on inline skates is trying to impress his girlfriend .
Act **26.10** True **neutral** Pred **neutral**

Pre a gentleman in a striped shirt gesturing with a stick - like object in his hand while passersby stare at him .
Hyp a gentleman in a striped shirt joyously gesturing
Act **24.58** True **neutral** Pred **neutral**

Unit 16

`(((((NOT hyp:wearing) AND pre:NN) AND (NOT hyp:sleeping)) AND (NOT hyp:sitting)) AND (NOT hyp:eating))`

IoU **0.387** w_{entail} 0.022 $w_{neutral}$ 0.010 w_{contra} -0.042

Pre a woman wearing a red scarf raises her hand as she walks in a parade .
Hyp a woman raises her hand as she walks in a parade for st. patrick 's day .
Act **32.96** True **neutral** Pred **neutral**

Pre a guy on inline skates with a white hat is on a yellow rail .
Hyp the guy on inline skates is trying to impress his girlfriend .
Act **29.88** True **neutral** Pred **neutral**

Pre three men ; one pedaling while playing drums , one playing piano and one both pedaling and steering , move a type of mobile band down a street .
Hyp three men are trying to attract a crowd and take them to a bar where they will be playing later
Act **28.13** True **neutral** Pred **neutral**

Unit 70

`((((hyp:in OR hyp:nobody) OR hyp:sitting) AND (NOT overlap-75%)) OR hyp:cat)`

IoU **0.164** w_{entail} -0.095 $w_{neutral}$ -0.019 w_{contra} 0.051

Pre many people have painted faces at night .
Hyp the people are swimming in the ocean at noon .
Act **39.61** True **contra** Pred **contra**

Pre a man is carrying a child while holding a red and blue umbrella .
Hyp a man is swimming laps in a pool .
Act **39.46** True **contra** Pred **contra**

Pre a man with a mustache is playing ice hockey with snow in the background .
Hyp people are swimming in the lake .
Act **38.12** True **contra** Pred **contra**

Unit 71

`(((((NOT hyp:to) AND pre:NN) AND (NOT hyp:for)) AND (NOT overlap-75%)) AND (NOT hyp:outdoors))`

IoU **0.366** w_{entail} 0.005 $w_{neutral}$ -0.049 w_{contra} 0.022

Pre a young man smiles and points at something off - camera , while standing in front of a display .
Hyp the young man is frowning with his hands in his pockets .
Act **37.08** True **contra** Pred **contra**

Pre a little boy in a blue shirt holding a toy .
Hyp boy dressed in red lighting things on fire .
Act **36.44** True **contra** Pred **contra**

Pre a shepherd breed dog running on the beach
Hyp a dog is at home sleeping
Act **36.19** True **contra** Pred **contra**

Unit 89

`(((((NOT overlap-50%) AND pre:NN) AND (NOT pre:for)) AND (NOT hyp:sitting)) AND (NOT hyp:wearing))`

IoU **0.251** w_{entail} -0.054 $w_{neutral}$ 0.015 w_{contra} 0.024

Pre a little girl with a hat sits between a woman 's feet in the sand in front of a pair of colorful tents .
Hyp the girl is related to the woman .
Act **33.38** True **neutral** Pred **neutral**

Pre two girls are sitting outside on the ground in front of a lake .
Hyp two girls waiting for butterflies
Act **30.10** True **neutral** Pred **neutral**

Pre three hockey players are in the middle of a play .
Hyp the players are playing for the championship
Act **27.38** True **neutral** Pred **neutral**

Unit 98

`((((NOT overlap-50%) AND (hyp:in OR hyp:running)) OR hyp:swimming) OR hyp:riding)`

IoU **0.127** w_{entail} -0.099 $w_{neutral}$ -0.035 w_{contra} 0.061

Pre a woman , wearing a dress , while sitting down playing a musical instrument and singing into a microphone .
Hyp the woman is swimming in the middle of the ocean by herself .
Act **35.66** True **contra** Pred **contra**

Pre a man with a mustache is playing ice hockey with snow in the background .
Hyp people are swimming in the lake .
Act **35.56** True **contra** Pred **contra**

Pre people walking through dirt .
Hyp people are swimming .
Act **32.38** True **contra** Pred **contra**

Unit 128

`(((((NOT overlap-50%) AND hyp:NN) AND (NOT hyp:outside)) OR hyp:sleeping) AND (NOT hyp:near))`

IoU **0.313** w_{entail} -0.035 $w_{neutral}$ 0.001 w_{contra} 0.034

Pre two men are on a cherry picker proceeding to perform work at a construction site .
Hyp two men driving in a truck down an empty highway .
Act **46.77** True **contra** Pred **contra**

Pre a woman dressed in a blue long - sleeved shirt and wearing a hairnet .

Hyp the woman is naked and alone in the bathroom .
Act **44.54** True **contra** Pred **contra**

Pre a boy in a red shirt and a boy in a yellow shirt are jumping on a trampoline outside .
Hyp the boys are asleep .
Act **42.99** True **contra** Pred **contra**

Unit 134

`((((NOT pre:blue) AND (hyp:. AND hyp:NN)) AND (NOT hyp:there)) AND (NOT hyp:outside))`

IoU **0.200** w_{entail} -0.055 $w_{neutral}$ 0.009 w_{contra} 0.038

Pre a man in a red hat and shirt with gray shorts attempts to do the splits .
Hyp the man has a blue hat .
Act **29.96** True **contra** Pred **contra**

Pre people walking down a busy city street in the winter .
Hyp people are running down a busy city street in summer .
Act **28.37** True **contra** Pred **contra**

Pre police officer and his motorcycle in a crowd of people at a protest .
Hyp a police officer is riding a unicorn in front of a crowd .
Act **27.77** True **contra** Pred **contra**

Unit 157

`((((hyp:for OR hyp:to) AND hyp:.) OR hyp:asleep) OR hyp:sad)`

IoU **0.150** w_{entail} -0.032 $w_{neutral}$ 0.026 w_{contra} -0.032

Pre a pale dog runs down a path .
Hyp a dog is running towards his owner
Act **21.24** True **neutral** Pred **neutral**

Pre a man in a black and blue jacket and a white helmet skiing down a hill swiftly .
Hyp a man goes down the ski hill swiftly because he is an expert .
Act **20.73** True **neutral** Pred **neutral**

Pre a woman wearing a red scarf raises her hand as she walks in a parade .
Hyp a woman raises her hand as she walks in a parade for st. patrick 's day .
Act **20.34** True **neutral** Pred **neutral**

Unit 173

`(((((NOT overlap-75%) AND hyp:IN) OR pre:sitting) OR pre:water) AND (NOT hyp:there))`

IoU **0.175** w_{entail} -0.085 $w_{neutral}$ -0.021 w_{contra} 0.035

Pre a mother and her two children sit down to rest .
Hyp three people are running around .
Act **31.63** True **contra** Pred **contra**

Pre a group of people sitting in a grassy area under a pink and white blossoming tree .
Hyp people are running in a grassy area .
Act **30.69** True **contra** Pred **contra**

Pre 3 people sitting in a boat , rowing in a large body of water surrounded by greenery .
Hyp the people standing in a train
Act **30.24** True **contra** Pred **contra**

Unit 203

`((((NOT overlap-50%) AND (hyp:in OR hyp:on)) OR hyp:sleeping) OR hyp:eating)`

IoU **0.167** w_{entail} -0.061 $w_{neutral}$ -0.009 w_{contra} 0.059

Pre a girl and two boys are playing in water .
Hyp the children are eating dinner at a restaurant .
Act **37.10** True **contra** Pred **contra**

Pre while some people look in the barn , others walk on the bridge and some are enjoying cooling off in the water by the beach .
Hyp the people are going in the barn to see the horse .
Act **34.58** True **neutral** Pred **contra**

Pre brown dog running through shallow water .
Hyp a dog is sleeping on a blanket .
Act **33.11** True **contra** Pred **contra**

Unit 257

`((((hyp:their OR overlap-75%) AND hyp:IN) OR hyp:friend) AND hyp:.)`

IoU **0.218** w_{entail} -0.041 $w_{neutral}$ 0.052 w_{contra} 0.003

Pre a dressed up woman walking next to a store at night .
Hyp a dressed up woman is walking next to a pharmacy at night .
Act **30.76** True **neutral** Pred **neutral**

Pre a man in a blue shirt , khaki shorts , ball cap and white socks and loafers walking behind a group of people walking down a stone walkway with a water bottle in his left hand .
Hyp a man in a blue shirt , khaki shorts , ball cap and blue socks and loafers walking behind a group of people walking down a stone walkway with a water bottle in his left hand .
Act **29.69** True **contra** Pred **contra**

Pre a man is standing in coconuts while trying to open one .
Hyp a sad man is standing in coconuts while trying to open one .
Act **29.24** True **neutral** Pred **neutral**

Unit 265

`(((((NOT hyp:PRP$) AND pre:.) AND (NOT hyp:VB)) AND (NOT hyp:PRP)) AND (NOT hyp:in))`

IoU **0.323** w_{entail} 0.028 $w_{neutral}$ -0.003 w_{contra} -0.055

Pre a youth is kicking a soccer ball in an empty brick area .
Hyp a human kicking .
Act **35.21** True **entail** Pred **entail**

Pre a band of people playing brass instruments is performing outside .
Hyp a group of people have instruments .
Act **31.93** True **entail** Pred **entail**

Pre three hikers are hiking in a mountain filled with trees and snow .
Hyp peopl;e were on grass
Act **31.77** True unknown Pred **entail**

Unit 270

`(((((NOT overlap-50%) AND hyp:DT) AND (NOT hyp:outside)) AND (NOT hyp:has)) AND (NOT hyp:near))`

IoU **0.315** w_{entail} -0.060 $w_{neutral}$ -0.011 w_{contra} 0.030

Pre several people prepare their stalls that consist of fish , vegetables and fruits for the public eye .
Hyp two men sit in a truck
Act **38.74** True **contra** Pred **contra**

Pre outdoors in front of a crowd , a man plays an instrument by blowing into pipes he holds up to his face .
Hyp a man sitting on the couch reading a book .
Act **34.87** True **contra** Pred **contra**

Pre blurry people walking in the city at night .
Hyp seven people dancing in a nightclub .
Act **34.41** True **contra** Pred **contra**

Unit 280

`(((((NOT hyp:for) AND pre:NN) AND (NOT hyp:VB)) AND (NOT hyp:PRP)) OR overlap-75%)`

IoU **0.420** w_{entail} 0.018 $w_{neutral}$ -0.034 w_{contra} 0.022

Pre the lady in the red jacket is helping the other lady decide what to buy .
Hyp there are multiple people present .
Act **30.85** True **entail** Pred **entail**

Pre a sports match is taking place between one team wearing the colors red and white and another team sporting the colors black and blue .
Hyp the two teams are wearing different colors .
Act **28.93** True **entail** Pred **entail**

Pre two men , one with a camera and another with hair clippers are helping another man in kitchen .
Hyp three men are pictured
Act **28.62** True **entail** Pred **entail**

Unit 283
`(((((NOT pre:and) AND hyp:IN) OR hyp:PRP$) AND hyp:.) OR hyp:VB)`
IoU **0.223** w_{entail} -0.086 $w_{neutral}$ 0.034 w_{contra} 0.010

Pre a soccer game with multiple males playing .
Hyp a men 's soccer team winning the world cup .
Act **32.36** True **neutral** Pred **neutral**

Pre a military group in uniform standing together while one of them gets their hat adjusted .
Hyp a drill instructor is adjusted a students hat before they preform at a funeral .
Act **29.43** True **neutral** Pred **neutral**

Pre a man is navigating a boat .
Hyp a man is steering a large yacht down the lake .
Act **28.63** True **neutral** Pred **neutral**

Unit 284
`(((((NOT hyp:JJ) AND overlap-25%) AND (NOT hyp:PRP$)) AND (NOT hyp:to)) OR hyp:people)`
IoU **0.185** w_{entail} 0.033 $w_{neutral}$ 0.022 w_{contra} -0.065

Pre elegantly dressed in black , a man and woman embrace in dance .
Hyp two people are dancing .
Act **26.72** True **entail** Pred **entail**

Pre two men on bicycles competing in a race .
Hyp people are riding bikes .
Act **22.49** True **entail** Pred **entail**

Pre people walking to a special place .
Hyp people are walking .
Act **21.08** True **entail** Pred **entail**

Unit 302
`((((hyp:for OR hyp:to) OR hyp:home) OR hyp:after) OR hyp:their)`
IoU **0.226** w_{entail} -0.053 $w_{neutral}$ 0.032 w_{contra} 0.004

Pre toddler walking along path .
Hyp toddler is walking to his mom
Act **33.80** True **neutral** Pred **neutral**

Pre uniformed schoolgirls are walking together on the street .
Hyp the girls are walking home from school .
Act **30.83** True **neutral** Pred **neutral**

Pre a pale dog runs down a path .
Hyp a dog is running towards his owner
Act **28.92** True **neutral** Pred **neutral**

Unit 362
`((((hyp:outdoors OR hyp:outside) OR hyp:near) OR hyp:there) OR hyp:not)`
IoU **0.188** w_{entail} 0.041 $w_{neutral}$ -0.027 w_{contra} -0.062

Pre man and a woman walking on the street
Hyp there are at least two people in the picture .
Act **36.00** True **entail** Pred **entail**

Pre three women are sitting on a wharf and kicking their feet in the water .
Hyp more than one person is touching a liquid .
Act **35.04** True **entail** Pred **entail**

Pre a group of people playing guitars and singing .
Hyp there are several people in this photo , and they are all making music .
Act **32.35** True **entail** Pred **entail**

Unit 375
`((((hyp:nobody OR overlap-75%) OR hyp:not) OR hyp:no) OR hyp:one)`
IoU **0.201** w_{entail} -0.007 $w_{neutral}$ -0.038 w_{contra} 0.089

Pre a band which includes an upright bass player is playing in a tent in front of canadian flags .
Hyp the band has no bass player .

Act **30.21** True **contra** Pred **contra**

Pre a boy with a concerned look it holding up two newspapers featuring a headline about murder .
Hyp a boy is not holding anything .
Act **25.75** True **contra** Pred **contra**

Pre a young boy wearing a red coat eats a chocolate bar .
Hyp the boy has no clothes on .
Act **20.98** True **contra** Pred **contra**

Unit 382

`(((((NOT hyp:there) AND hyp:NN) AND (NOT hyp:sitting)) AND (NOT hyp:standing)) OR hyp:VB)`

IoU **0.375** w_{entail} -0.022 $w_{neutral}$ 0.024 w_{contra} 0.008

Pre a group of people wearing hats and using walking sticks are walking through a wooded area on a trail .
Hyp the tourists are being guided on their trip .
Act **40.71** True **neutral** Pred **neutral**

Pre a gentleman in a striped shirt gesturing with a stick - like object in his hand while passersby stare at him .
Hyp a gentleman in a striped shirt joyously gesturing
Act **40.40** True **neutral** Pred **neutral**

Pre a middle - aged man in a gray t - shirt and brown pants sitting on his bed reading a flyer - like paper .
Hyp he is reading a flyer about a new job he is interested in .
Act **40.04** True **neutral** Pred **neutral**

Unit 386

`((((hyp:IN AND overlap-75%) OR hyp:not) OR hyp:no) OR hyp:only)`

IoU **0.198** w_{entail} -0.075 $w_{neutral}$ 0.014 w_{contra} 0.060

Pre a man in a blue shirt , khaki shorts , ball cap and white socks and loafers walking behind a group of people walking down a stone walkway with a water bottle in his left hand .
Hyp a man in a blue shirt , khaki shorts , ball cap and blue socks and loafers walking behind a group of people walking down a stone walkway with a water bottle in his left hand .
Act **32.64** True **contra** Pred **contra**

Pre a boy with a concerned look it holding up two newspapers featuring a headline about murder .
Hyp a boy is not holding anything .
Act **26.37** True **contra** Pred **contra**

Pre a dressed up woman walking next to a store at night .
Hyp a dressed up woman is walking next to a pharmacy at night .
Act **25.10** True **neutral** Pred **neutral**

Unit 390

`((((hyp:IN OR hyp:to) OR hyp:PRP$) AND (NOT hyp:EX)) OR hyp:NNP)`

IoU **0.422** w_{entail} -0.045 $w_{neutral}$ 0.033 w_{contra} 0.010

Pre two women walking in an area of UNK .
Hyp two UNK workers walk down the street of the once beautiful suburban neighborhood , surveying the damage from the storm .
Act **41.84** True **neutral** Pred **neutral**

Pre a group of kids are playing on a tire swing .
Hyp a group of dogs are chasing a duck .
Act **39.84** True **contra** Pred **contra**

Pre a woman walks by a brick building that 's covered with graffiti .
Hyp the woman 's son drew some of the graffiti .
Act **37.97** True **neutral** Pred **neutral**