

# Making sense of hidden neuron activations with deductive reasoning



**Pascal Hitzler**

Data Semantics Laboratory (DaSe Lab)  
Kansas State University

<http://www.daselab.org>

# Neuro-symbolic AI

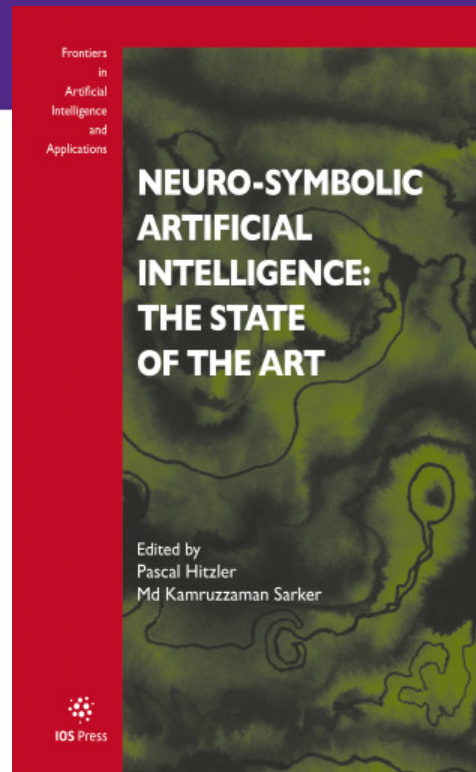
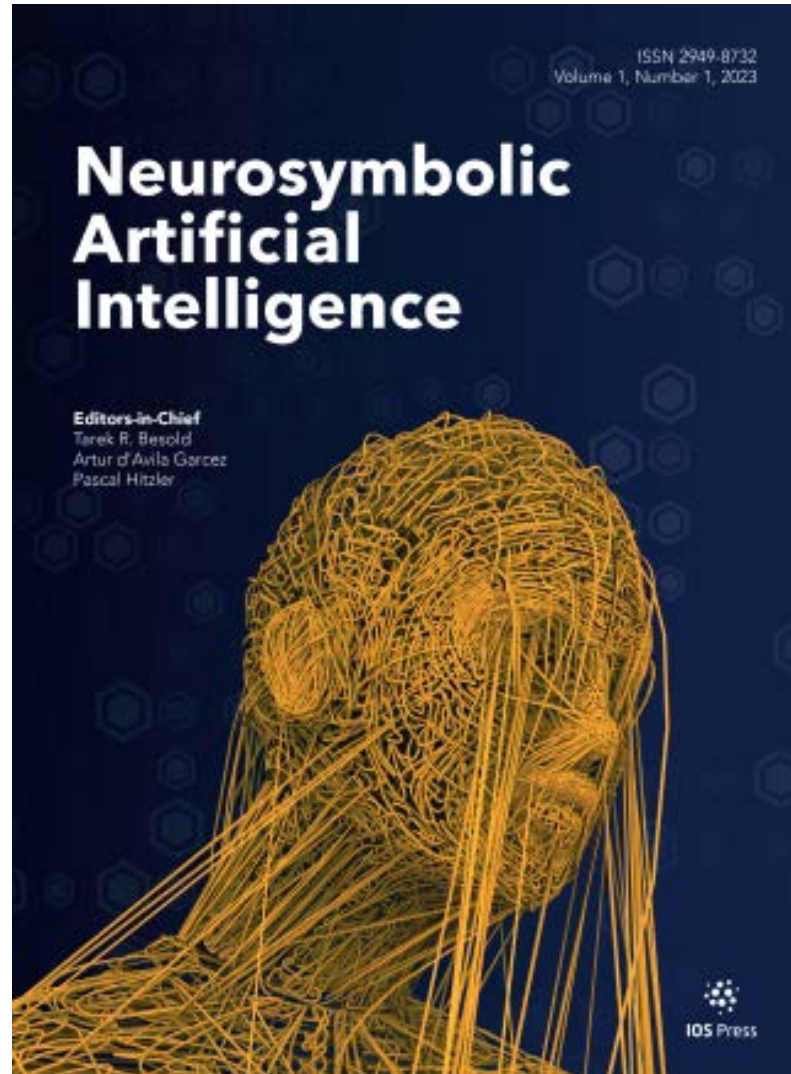


## Publications on neuro-symbolic AI in major conferences (research papers only):

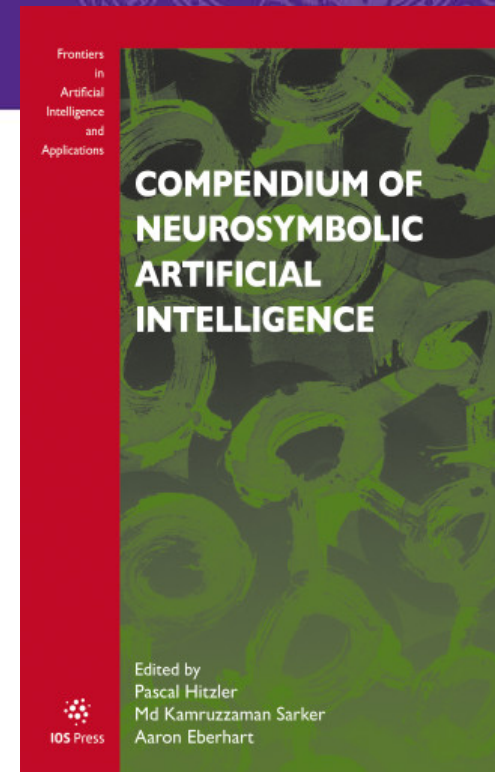
conference	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	total
ICML	0	0	0	0	0	1	3	2	5	6	17
NeurIPS	0	0	0	0	0	0	0	4	2	4	10
AAAI	0	0	0	0	0	1	0	1	1	1	4
IJCAI	1	0	0	0	0	0	2	2	0	2	7
ICLR	N/A	N/A	0	0	0	0	1	1	1	3	6
total	1	0	0	0	0	2	6	10	9	16	44

See

**Md Kamruzzaman Sarker, Lu Zhou, Aaron Eberhart, Pascal Hitzler**  
**Neuro-Symbolic Artificial Integration: Current Trends**  
**AI Communications 34 (3), 197-209, 2022.**



2022, 17 chapters



2023, 30 chapters

**Neurosymbolic AI community slack  
currently 770 members  
email [hitzler@ksu.edu](mailto:hitzler@ksu.edu) to get an invite**

# **Problem setting: why we need strong explainability for deep learning systems**

# The black box problem



**There have been enormous strides recently in methods and applications of Deep learning.**

**However**

- **Deep Learning system are black boxes**
- **Evaluation is only done statistically**

**This is insufficient for many application areas, and problematic for most.**

# The black box problem



## COVID-19 detection

Subject No	Subject Image	Rendered Image (20x20 pixels)
1 COVID		
2 Normal		
3 pneumonia bacterial		
4 pneumonia Viral		

## Gastrointestinal disease detection (Kvasir dataset)

Class	Original image	20x20 rendered image	Class	Original Image	20x20 image
1			1		
2			2		
3			3		
4			4		
5			5		
6			6		

CNN classification accuracy:

Original images – 77%  
 Blank background images – 41%  
 Mere chance accuracy – 12%

CNN classification accuracy:

Original images – 67%  
 Blank background images – 62%  
 Mere chance accuracy – 25%

## Face recognition (Yale B)

Subject ID	Original Image	Rendered image (27x20)	Subject ID	Original image	Rendered image (27x20)	Subject ID	Original Image	Rendered image (27x20)
1			3			5		
2			4					

CNN classification accuracy:

Original images – 99%  
 Blank background images – 87%  
 Mere chance accuracy – 4%

Dhar, S., Shamir, L., 2021, *Visual Informatics*, 5(3), 92-101 – thanks to Lior Shamir for the slides input



# Galaxy image annotation



Classification to spiral galaxies and elliptical galaxies

When the test set and training set are from the same part of the sky, the CNN shows a different Universe than when the training and test images come from different parts of the sky.



e Lab

## SDSS



Training set and test set from the same part of the sky

	Elliptical	Spiral
Elliptical	2891	109
Spiral	85	2915

Training set and test set from different parts of the sky

	Elliptical	Spiral
Elliptical	2704	296
Spiral	31	2969

## Pan-STARRS



Training set and test set from the same part of the sky

	Elliptical	Spiral
Elliptical	7850	150
Spiral	756	7244

Training set and test set from different parts of the sky

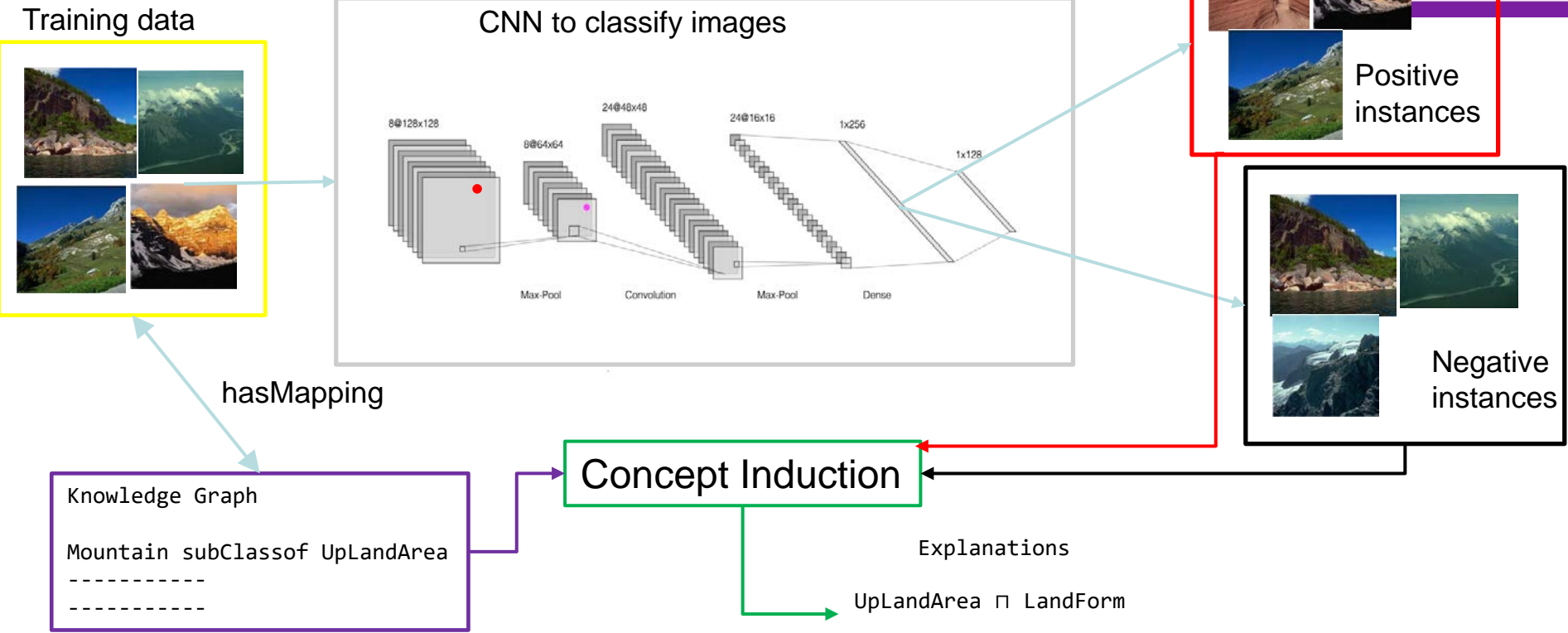
	Elliptical	Spiral
Elliptical	7699	301
Spiral	450	7550

Dhar, S., Shamir, L., 2022, *Astronomy and Computing*, 38, 100545

# Approach: Concept Induction for Hidden Layer Analysis



# Idea



**New results based on: Abhilekha Dalal, Md Kamruzzaman Sarker, Adrita Barua, Eugene Vasserman, Pascal Hitzler, manuscript in preparation.**

# Concept Induction

Some slides adapted from Joshua Schwartz, with permission.

# Concept Induction

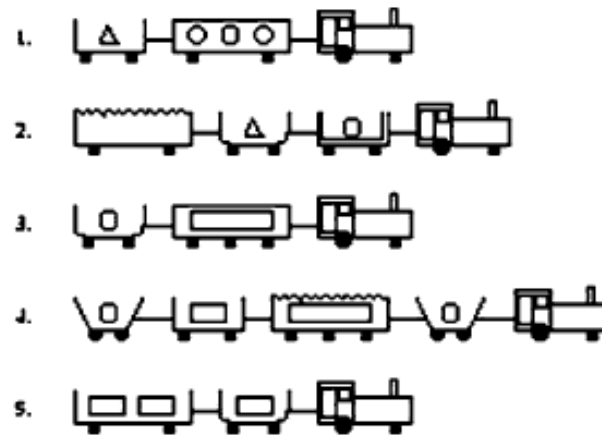


Approach similar to inductive logic programming, but using Description Logics (the logic underlying OWL).

Positive examples:

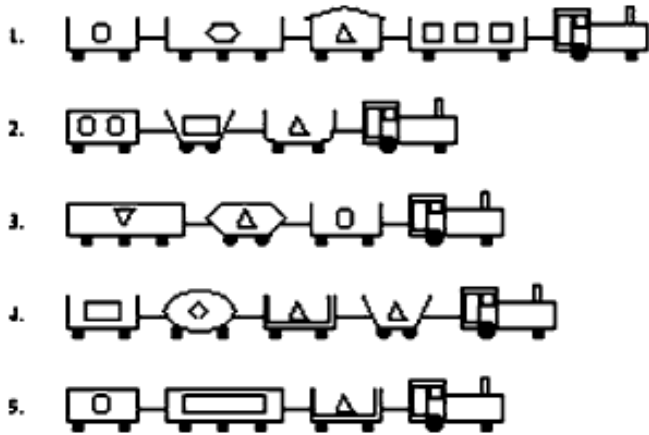


negative examples:

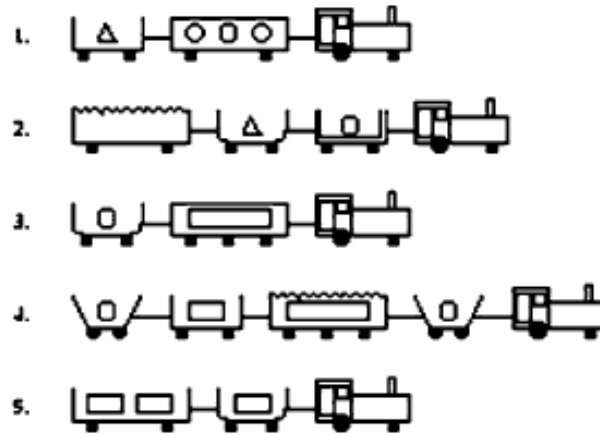


Task: find a class description (logical formula) which separates positive and negative examples.

Positive examples:



negative examples:



DL-Learner result:  $\exists \text{hasCar} . (\text{Closed} \sqcap \text{Short})$

In FOL:  $\{x \mid \exists y (\text{hasCar}(x, y) \wedge \text{Closed}(y) \wedge \text{Short}(y))\}$

Theory and system: [Lehmann & Hitzler 2010], DL-Learner

```
car(car_11).  car(car_12).  car(car_13).
car(car_14).
car(car_21).  car(car_22).  car(car_23).
car(car_31).  car(car_32).  car(car_33).
car(car_41).  car(car_42).  car(car_43).
car(car_44).
car(car_51).  car(car_52).  car(car_53).
car(car_61).  car(car_62).
car(car_71).  car(car_72).  car(car_73).
car(car_81).  car(car_82).
car(car_91).  car(car_92).  car(car_93).
car(car_94).
car(car_101).  car(car_102).

train(east1).  train(east2).  train(east3).
train(east4).  train(east5).
train(west6).  train(west7).  train(west8).
train(west9).  train(west10).
```

```
// eastbound train 1
```

```
has_car(east1,car_11).
has_car(east1,car_12).
has_car(east1,car_13).
has_car(east1,car_14).

short(car_12).
closed(car_12).
long(car_11).
long(car_13).
short(car_14).
open_car(car_11).
open_car(car_13).
open_car(car_14).
shape(car_11,rectangle).
shape(car_12,rectangle).
shape(car_13,rectangle).
shape(car_14,rectangle).
load(car_11,rectangle).
load_count(car_11,three).
load(car_12,triangle).
load_count(car_12,one).
load(car_13,hexagon).
load_count(car_13,one).
load(car_14,circle).
load(car_14,one).
wheels(car_11,two).
wheels(car_12,two).
wheels(car_13,three).
wheels(car_14,two).
```

## Somewhat more formally...

generating complex description logic class expressions  $S$  from a given description logic knowledge base (or ontology)  $\mathcal{O}$  and sets  $P$  and  $N$  of instances, understood as positive and negative examples, such that  $\mathcal{O} \models S(a)$  for all  $a \in P$ , and  $\mathcal{O} \not\models S(b)$  for all  $b \in N$



# Algorithmically – Refinement Operator

Start with simple formula  $E$  (e.g.,  $\top$ )

Loop: Expand  $E$  minimally in all possible ways to  
 $E_1, \dots, E_n$

Check accuracy for  $E_1$  through  $E_n$  regarding  $P$  and  $N$

Replace  $E$  by highest-scoring  $E_i$

Exit loop if perfect solution found or other stopping  
criteria met

Return  $E$

In reality, a list of formulas is returned, ranked by accuracy.

Accuracy can be f-measure, precision, recall, etc.

**Checking accuracy needs deductive reasoning, i.e., is expensive.**

[Lehmann & Hitzler, Machine Learning, 2010], DL-Learner system



# Algorithmically – heuristic

- Restrict allowed syntax expansions (e.g., conjunctions only)
- Restrict complexity of logic in background knowledge (e.g., class hierarchy only)

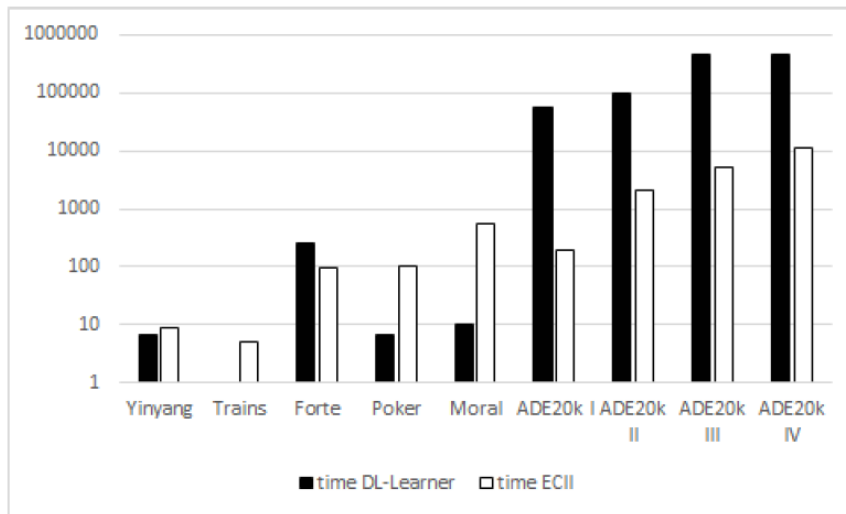


Figure 1: Runtime comparison between DL-Learner and ECII. The vertical scale is logarithmic in hundredths of seconds, and note that DL-Learner runtime has been capped at 4,500 seconds for ADE20k III and IV. For ADE20k I it was capped at each run at 600 seconds.

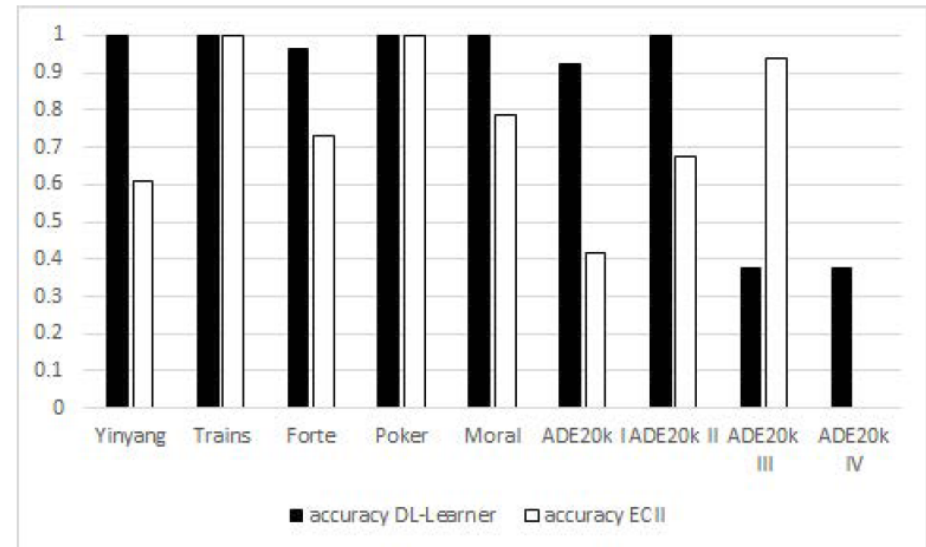


Figure 2: Accuracy ( $\alpha_3$ ) comparison between DL-Learner and ECII. For ADE20k IV it was not possible to compute an accuracy score within 3 hours for ECII as the input ontology was too large.

**[Sarker & Hitzler, AAI, 2019]: ECII system**

# Background Knowledge

# Background knowledge



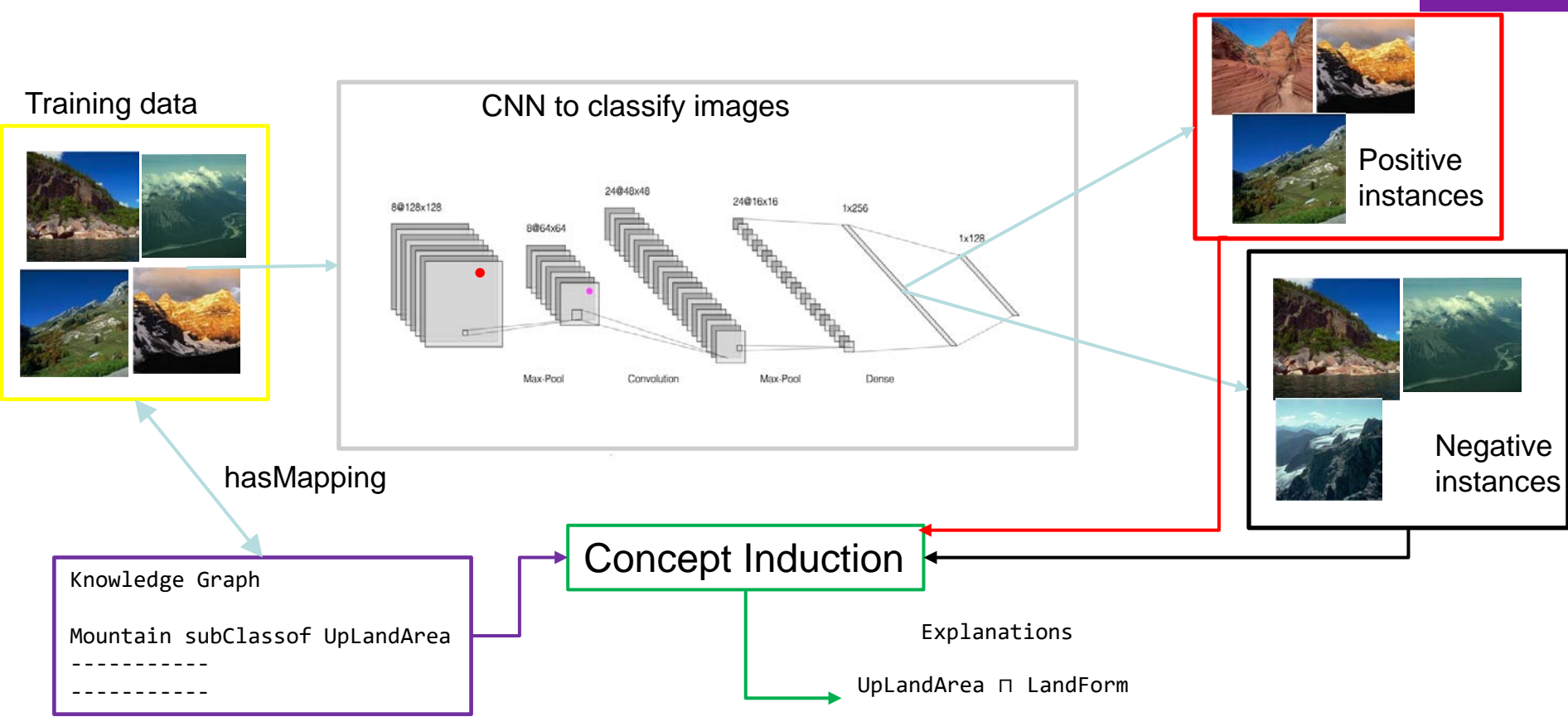
- **Based on Wikipedia category hierarchy**
  - **which is not a hierarchy because it has loops, caused by crowd-sourcing**
- **Heuristically curated by removing loops**
- **Resulting class hierarchy has approx. 2M concepts**
- **Broad coverage (all things in Wikipedia)**
- **Can easily refer to it from instances by mapping to Wikipedia pages and looking up the page categories.**

**[Sarker et al., KGSWC2020]**



# Concrete Setting

# Idea





# Scenario



- **Scene recognition (from images)**
- **MIT ADE20k dataset**  
<http://groups.csail.mit.edu/vision/datasets/ADE20K/>
- **10 overlapping scenes selected for our study**
- **Resnet50V2 trained (best of those we tried)**
  - **Training accuracy 87.6%**
  - **Validation accuracy 86.5%**

# Images annotations

The ADE20k images come with annotations of objects in the picture:

```
001 # 0 # 0 # sky # sky # ""
002 # 0 # 0 # road, route # road # ""
005 # 0 # 0 # sidewalk, pavement # sidewalk # ""
006 # 0 # 0 # building, edifice # building # ""
007 # 0 # 0 # truck, motortruck # truck # ""
008 # 0 # 0 # hovel, hut, hutch, shack, shanty # hut # ""
009 # 0 # 0 # pallet # pallet # ""
011 # 0 # 0 # box # boxes # ""
001 # 1 # 0 # door # door # ""
002 # 1 # 0 # window # window # ""
009 # 1 # 0 # wheel # wheel # ""
```



We ignore everything but the types of object on each image.

# Mapping to Background Knowledge



- **String matching (Levenshtein with edit distance 0) from object types to Wikipedia categories**

**contains(img1,road1)**

**contains(img1, window1)**

**contains(img1, door1)**

**contains(img1, wheel1)**

**contains(img1, sidewalk1)**

**contains(img1, truck1)**

**contains(img1, box1)**

**contains(img1, building1)**





# Label Hypothesis Generation and Confirmation

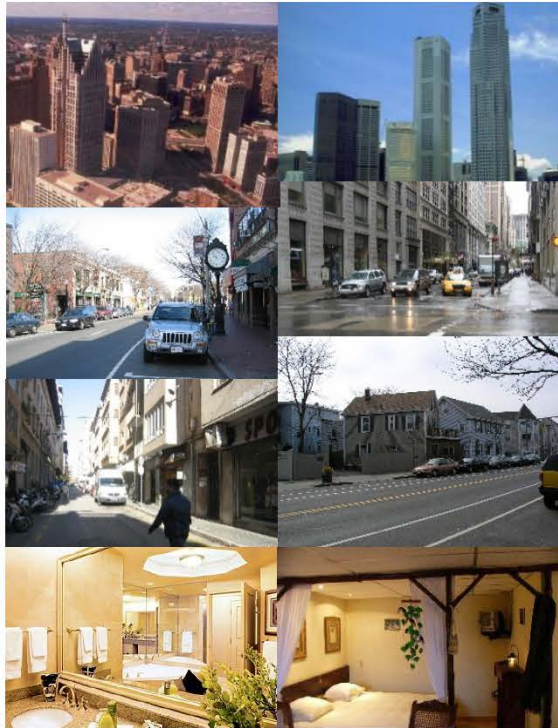
# Trained CNN



- **Scene classification on ADE20k**
- **Resnet50V2; 64 hidden nodes in the dense layer**

	<b>precision</b>	<b>recall</b>	<b>f1-score</b>	<b>support</b>
<b>bathroom</b>	<b>0.90</b>	<b>0.78</b>	<b>0.84</b>	<b>134</b>
<b>bedroom</b>	<b>0.89</b>	<b>0.88</b>	<b>0.88</b>	<b>277</b>
<b>building_facade</b>	<b>0.68</b>	<b>0.60</b>	<b>0.64</b>	<b>45</b>
<b>conference_room</b>	<b>0.77</b>	<b>0.91</b>	<b>0.83</b>	<b>33</b>
<b>dining_room</b>	<b>0.75</b>	<b>0.84</b>	<b>0.79</b>	<b>82</b>
<b>highway</b>	<b>0.96</b>	<b>0.88</b>	<b>0.92</b>	<b>59</b>
<b>kitchen</b>	<b>0.84</b>	<b>0.87</b>	<b>0.86</b>	<b>130</b>
<b>living_room</b>	<b>0.76</b>	<b>0.74</b>	<b>0.75</b>	<b>139</b>
<b>skyscraper</b>	<b>0.90</b>	<b>0.88</b>	<b>0.89</b>	<b>64</b>
<b>street</b>	<b>0.92</b>	<b>0.96</b>	<b>0.94</b>	<b>407</b>
<b>accuracy</b>			<b>0.87</b>	<b>1370</b>
<b>macro avg</b>	<b>0.84</b>	<b>0.83</b>	<b>0.83</b>	<b>1370</b>
<b>weighted avg</b>	<b>0.87</b>	<b>0.87</b>	<b>0.87</b>	<b>1370</b>





ADE20K DATASET



Positive Images

Classify images  
as positive (above)  
as negative (below) →

Collect new images using  
keyword "cross\_walk" →



Negative Images



GOOGLE IMAGES DATASET FOR NEURON 1

Figure 1: Example of images that were used for generating and confirming the label hypothesis for neuron 1

**workflow: label hypothesis generation and confirmation of label hypothesis with new images from Google images**



Neuron #	Obtained Label(s)	Images	Coverage	Target %	Non-Target %
<b>0</b>	<b>building</b>	<b>164</b>	<b>0.997</b>	<b>89.024</b>	<b>72.328</b>
<b>1</b>	<b>cross_walk</b>	<b>186</b>	<b>0.994</b>	<b>88.710</b>	<b>28.923</b>
<b>3</b>	<b>night_table</b>	<b>157</b>	<b>0.987</b>	<b>90.446</b>	<b>56.714</b>
6	dishcloth, toaster	106	0.999	16.038	39.078
7	toothbrush, Pipage	112	0.991	75.893	59.436
<b>8</b>	<b>shower_stall, cistern</b>	<b>136</b>	<b>0.995</b>	<b>100.000</b>	<b>53.186</b>
11	river_water	157	0.995	31.847	22.309
12	baseboard, dish_rag	108	0.993	75.926	48.248
14	rocking_horse, rocker	86	0.985	54.651	47.816
<b>16</b>	<b>mountain, bushes</b>	<b>108</b>	<b>0.995</b>	<b>87.037</b>	<b>24.969</b>
17	stem	133	0.993	30.827	31.800
<b>18</b>	<b>slope</b>	<b>139</b>	<b>0.983</b>	<b>92.086</b>	<b>69.919</b>
<b>19</b>	<b>wardrobe, air_conditioning</b>	<b>110</b>	<b>0.999</b>	<b>89.091</b>	<b>65.034</b>
20	fire_hydrant	158	0.990	5.696	13.233
<b>22</b>	<b>skyscraper</b>	<b>156</b>	<b>0.992</b>	<b>99.359</b>	<b>54.893</b>
23	fire_escape	162	0.996	61.111	18.311
25	spatula, nuts	126	0.999	2.381	0.883
26	skyscraper, river	112	0.995	77.679	35.489
27	manhole, left_arm	85	0.996	35.294	26.640
28	flooring, fluorescent_tube	115	1.000	38.261	33.198
<b>29</b>	<b>lid, soap_dispenser</b>	<b>131</b>	<b>0.998</b>	<b>99.237</b>	<b>78.571</b>
<b>30</b>	<b>teapot, saucepan</b>	<b>108</b>	<b>0.998</b>	<b>81.481</b>	<b>47.984</b>
<b>31</b>	fire_escape	162	0.961	77.160	63.147
33	tanklid, slipper	81	0.987	41.975	30.214
34	left_foot, mouth	110	0.994	20.909	49.216

Neuron #	Obtained Label(s)	Images	Coverage	Target %	Non-Target %
35	utensils_canister, body	111	0.999	7.207	11.223
<b>36</b>	<b>tap, crapper</b>	<b>92</b>	<b>0.997</b>	<b>89.130</b>	<b>70.606</b>
37	cistern, doorcase	101	0.999	21.782	24.147
38	letter_box, go_cart	125	0.999	28.000	31.314
39	side_rail	148	0.980	35.811	34.687
40	sculpture, side_rail	119	0.995	25.210	21.224
<b>41</b>	<b>open_fireplace, coffee_table</b>	<b>122</b>	<b>0.992</b>	<b>88.525</b>	<b>16.381</b>
42	pillar, stretcher	117	0.998	52.137	42.169
<b>43</b>	<b>central_reservation</b>	<b>157</b>	<b>0.986</b>	<b>95.541</b>	<b>84.973</b>
44	saucepan, dishrack	120	0.997	69.167	36.157
46	Casserole	157	0.999	45.223	36.394
<b>48</b>	<b>road</b>	<b>167</b>	<b>0.984</b>	<b>100.000</b>	<b>73.932</b>
<b>49</b>	<b>footboard, chain</b>	<b>126</b>	<b>0.982</b>	<b>88.889</b>	<b>66.702</b>
50	night_table	157	0.972	65.605	62.735
<b>51</b>	<b>road, car</b>	<b>84</b>	<b>0.999</b>	<b>98.810</b>	<b>48.571</b>
53	pylon, posters	104	0.985	11.538	17.332
<b>54</b>	<b>skyscraper</b>	<b>156</b>	<b>0.987</b>	<b>98.718</b>	<b>70.432</b>
<b>56</b>	<b>flusher, soap_dish</b>	<b>212</b>	<b>0.997</b>	<b>90.094</b>	<b>63.552</b>
<b>57</b>	<b>shower_stall, screen_door</b>	<b>133</b>	<b>0.999</b>	<b>98.496</b>	<b>31.747</b>
58	plank, casserole	80	0.998	3.750	3.925
59	manhole, left_arm	85	0.994	35.294	21.589
60	paper_towels, jar	87	0.999	0.000	1.246
61	ornament, saucepan	102	0.995	43.137	17.274
62	sideboard	100	0.991	21.000	29.734
<b>63</b>	<b>edifice, skyscraper</b>	<b>178</b>	<b>0.999</b>	<b>92.135</b>	<b>48.761</b>



# Evaluation

# Approach



- **Each row of the table is a hypothesis, e.g. “neuron 1 activates more strongly on cross\_walk images (retrieved from Google images using keyword “cross\_walk”) than on other images.”**
- **Null hypothesis: There is no difference in activations.**
- **There is no reason to assume a normal distribution,**
- **hence using Mann-Whitney U test for assessment.**

# Evaluation results

Neuron #	Label(s)	Images	# Activations (%)		Mean		Median		z-score	p-value
			targ	non-t	targ	non-t	targ	non-t		
0	building	42	80.95	73.40	2.08	1.81	2.00	1.50	-1.28	0.0995
1	cross_walk	47	91.49	28.94	4.17	0.67	4.13	0.00	-8.92	<.00001
3	night_table	40	100.00	55.71	2.52	1.05	2.50	0.35	-6.84	<.00001
8	shower_stall, cistern	35	100.00	54.40	5.26	1.35	5.34	0.32	-8.30	<.00001
16	mountain, bushes	27	100.00	25.42	2.33	0.67	2.17	0.00	-6.72	<.00001
18	slope	35	91.43	68.85	1.59	1.37	1.44	1.00	-2.03	0.0209
19	wardrobe, air_conditioning	28	89.29	65.81	2.30	1.28	2.30	0.84	-4.00	<.00001
22	skyscraper	39	97.44	56.16	3.97	1.28	4.42	0.33	-7.74	<.00001
29	lid, soap_dispenser	33	100.00	80.47	4.38	2.14	4.15	1.74	-5.92	<.00001
30	teapot, saucepan	27	85.19	49.93	2.52	1.05	2.23	0.00	-4.28	<.00001
36	tap, crapper	23	91.30	70.78	3.24	1.75	2.82	1.29	-3.59	<.00001
41	open_fireplace, coffee_table	31	80.65	15.11	2.03	0.14	2.12	0.00	-7.15	<.00001
43	central_reservation	40	97.50	85.42	7.43	3.71	8.08	3.60	-5.94	<.00001
48	road	42	100.00	74.46	6.15	2.68	6.65	2.30	-7.78	<.00001
49	footboard, chain	32	84.38	66.41	2.63	1.67	2.30	1.17	-2.58	0.0049
51	road, car	21	100.00	47.65	5.32	1.52	5.62	0.00	-6.03	<.00001
54	skyscraper	39	100.00	71.78	4.14	1.61	4.08	1.12	-7.60	<.00001
56	flusher, soap_dish	53	92.45	64.29	3.47	1.48	3.08	0.86	-6.47	<.00001
57	shower_stall, screen_door	34	97.06	32.31	2.60	0.61	2.53	0.00	-7.55	<.00001
63	edifice, skyscraper	45	88.89	48.38	2.41	0.83	2.36	0.00	-6.73	<.00001

Table 3: Evaluation details as discussed in Section 4. Images: number of images used for evaluation. # Activations: (targ(et)): Percentage of target images activating the neuron (i.e., activation at least 80% of this neuron’s activation maximum); (non-t): Same for all other images used in the evaluation. Mean/Median (targ(et)/non-t(arget)): mean/median activation value for target and non-target images.

# Discussion





-target images not activating neuron 1



Non-target images activating neuron 1

Figure 2: Examples of some Google images used: target images (“cross\_walk”) that did not activate the neuron; non-target images from labels like “central\_reservation,” “road and car,” and “fire\_hydrant” that activated the neuron.

**Note: “bushes, bush” is the third-highest concept induction output (coverage 0.993; 48.052% of target images activating the neuron)**



# Going forward

We would really want to have labels with high target activation and low non-target activation.

- make use of more concept induction results
- better background knowledge
- optimize parameters (like thresholds)
- investigate neuron ensembles (●)

Label(s)	Images	# Activations (%)	
		targ	non-t
● building	42	80.95	73.40
cross_walk	47	91.49	28.94
night_table	40	100.00	55.71
shower_stall, cistern	35	100.00	54.40
mountain, bushes	27	100.00	25.42
slope	35	91.43	68.85
wardrobe, air_conditioning	28	89.29	65.81
● skyscraper	39	97.44	56.16
lid, soap_dispenser	33	100.00	80.47
teapot, saucepan	27	85.19	49.93
tap, crapper	23	91.30	70.78
open_fireplace, coffee_table	31	80.65	15.11
central_reservation	40	97.50	85.42
road	42	100.00	74.46
footboard, chain	32	84.38	66.41
road, car	21	100.00	47.65
● skyscraper	39	100.00	71.78
flusher, soap_dish	53	92.45	64.29
shower_stall, screen_door	34	97.06	32.31
● edifice, skyscraper	45	88.89	48.38

# Concluding



- **It works!**
- **But it needs to be refined.**



**Thanks!**

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**New results based on: Abhilekha Dalal, Md Kamruzzaman Sarker, Adrita Barua, Eugene Vasserman, Pascal Hitzler, manuscript in preparation.**



**Thanks!**