How a General-Purpose Commonsense Ontology can Improve Performance of Learning-Based Image Retrieval

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Summary

Motivation

Computer Vision

Simple $\rightarrow$ Complex

Computer Vision

Image classification: Kitchen

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Image captioning: "a woman in a chef coat holding bread loaves"

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Computer Vision

- Simple → Complex
- Learning everything from examples

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It does not scale (96.4% classification → 32.2% captioning)

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Idea: Prior knowledge can fill the holes in our datasets.

Prior Knowledge in Computer Vision

Main research trends

- Small hand-crafted ontologies
- Free form text (e.g. Wikipedia)
- Lexical ontologies (e.g. WordNet)

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What about commonsense ontologies, such as ConceptNet?

ConceptNet (CN)

CN is a commonsense ontology.

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Format

$\text{Concept}_1 - \text{Relation type} \rightarrow \text{Concept}_2$

Relation types

AtLocation, HasProperty, IsA, SimilarSize, UsedFor, CapableOf, ...

ConceptNet

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CN is a commonsense ontology.

Format

Concept_1 – Relation type $\rightarrow$ Concept_2

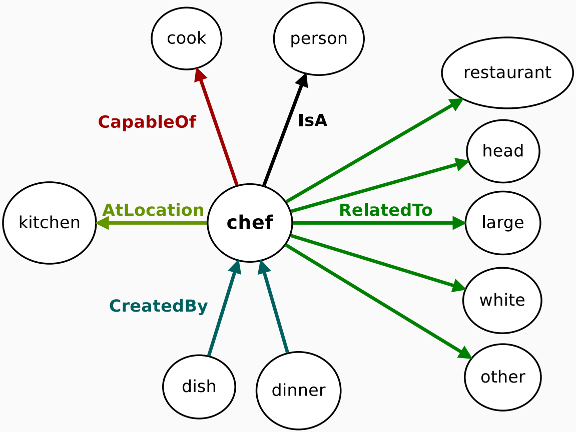
Relation types

AtLocation, HasProperty, IsA, SimilarSize, UsedFor, CapableOf, ...

Examples

desk – RelatedTo $\rightarrow$ office
computer – AtLocation $\rightarrow$ office
office – UsedFor $\rightarrow$ work
... and 8 million more

ConceptNet



cook
person
restaurant
CapableOf
IsA
head
kitchen
AtLocation
chef
RelatedTo
large
white
CreatedBy
dish
dinner
other

ConceptNet

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- CN has millions of assertions (vs hand-crafted ontologies)
- CN provides key knowledge to computers (vs Wikipedia)
- CN is a rich source of commonsense knowledge (vs WordNet)
- CN is simple to use (vs CYC)

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Previous works

ConceptNet in Computer Vision

Task	w/o CN	w/ CN	CN gain
Image Tagging Xie and He (2013)	7.3%	7.6%	**0.3%**
Video Retrieval de Boer et al. (2016)	3.9%	3.1%	**-0.8%**
Image Riddles Aditya et al. (2016)	68.0%	68.7%	**0.7%**

More examples: Bicocchi et al. (2012), Le et al. (2013), others

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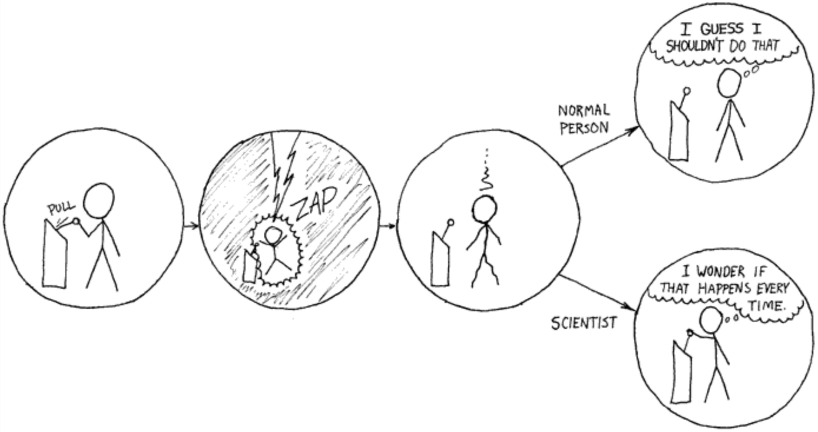
... but we wanted to give CN another try.

… because we are scientists



Source: https://xkcd.com/242/

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Sentence Based Image Retrieval

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Rank *n* images according to their *relevance*
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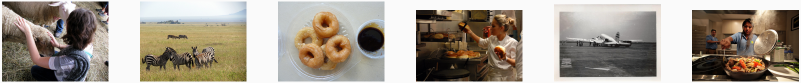

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Baseline

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We used the 1000 Concept detectors trained by Fang et al.

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Prob	Concept
0.996	kitchen
0.920	preparing
0.800	food
0.796	cooking
0.590	making
...	...
0.236	woman

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t = "a **woman** in a chef **coat holding bread** loaves"

$\mathbf{MIL}(t, I) = \mathrm{P}(\text{woman}|I) \cdot \mathrm{P}(\text{coat}|I) \cdot \mathrm{P}(\text{holding}|I) \cdot \mathrm{P}(\text{bread}|I)$

Baseline

$t =$ "a woman in a chef coat holding bread loaves"


1


2


3


4

...


512

$$\textbf{MIL}(t, I) = \mathrm{P}(\text{woman}|I) \cdot \mathrm{P}(\text{coat}|I) \cdot \mathrm{P}(\text{holding}|I) \cdot \mathrm{P}(\text{bread}|I)$$

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What are the limitations of this approach?

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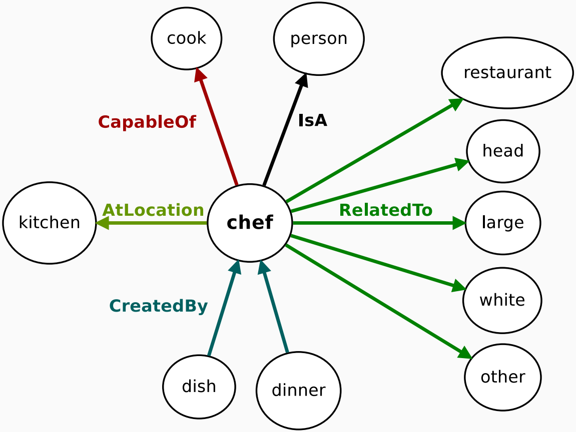
What are the limitations of this approach?

How can we detect a *chef* without a *chef* detector?

Baseline + ConceptNet



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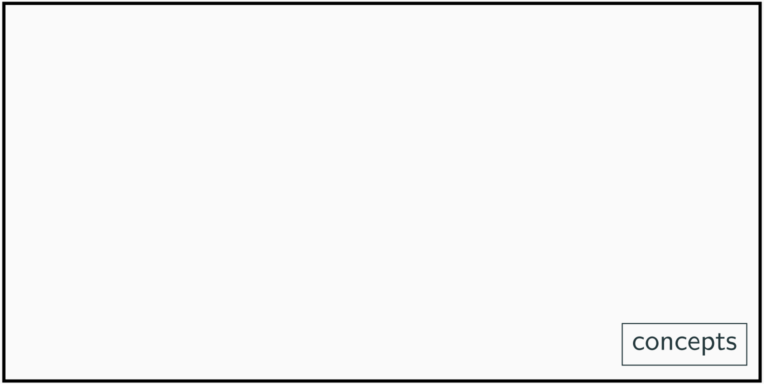
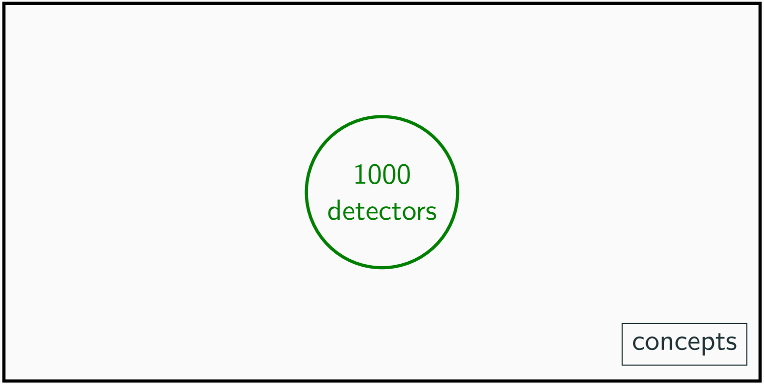


Idea: Augment the set of detectors using CN

Baseline + ConceptNet



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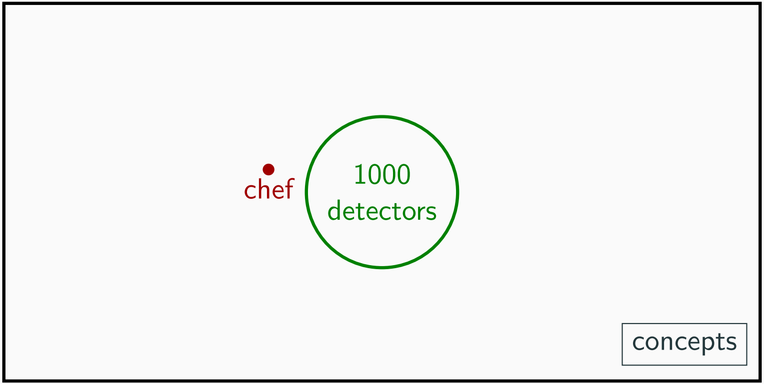

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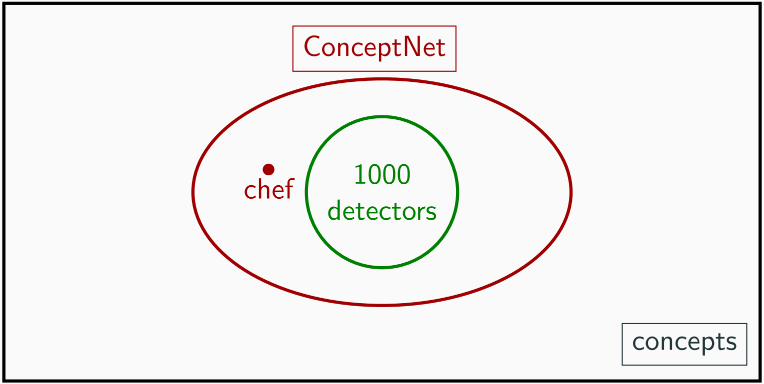

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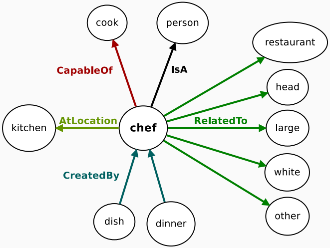
CN Score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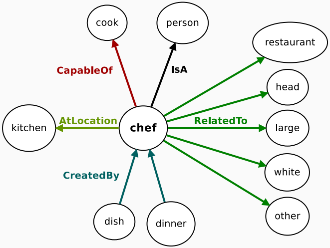
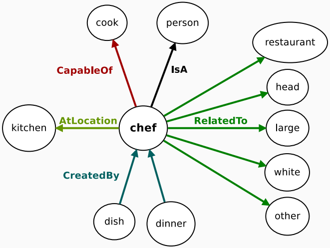


Word	Prob	Word	Prob
kitchen	0.996	dish	0.126
cook	0.796	white	0.091
restaurant	0.374	other	0.043
person	0.340	dinner	0.023
large	0.152	head	0.003

CN Score



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$$\mathrm{CN}_{\mathrm{MIN}}(\mathrm{chef}) = 0.003$$
$$\mathrm{CN}_{\mathrm{AVG}}(\mathrm{chef}) = 0.294$$
$$\mathrm{CN}_{\mathrm{MAX}}(\mathrm{chef}) = 0.996$$

CN Score

Database ⊂ COCO 5K	r@1	r@5	r@10	median rank	mean rank
Baseline					
MIL	**13.2**	33.4	45.2	**13**	82.2
CN					
CN_{MIN}	12.2	31.4	43.4	15	77.0
CN_{AVG}	**13.2**	**33.7**	**46.0**	**13**	**66.3**
CN_{MAX}	12.2	32.1	44.1	14	73.0
CN Gain	**0.0%**	**0.3%**	**0.8%**	**0**	**15.9**

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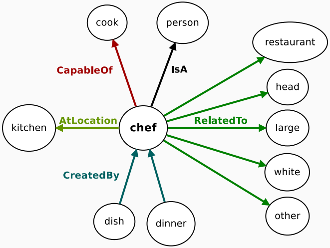

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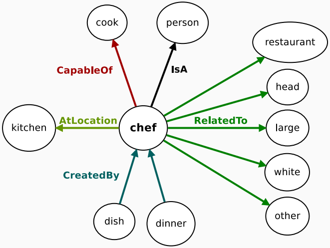
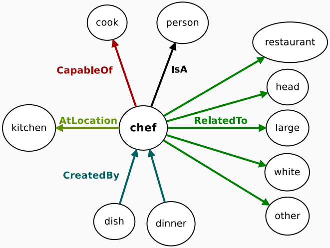


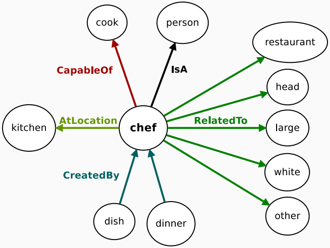
$P_c(\text{chef}|I)$

CN + ESPGAME Score



$$P_c(\text{chef}|I) = P(\text{chef}|\text{cook}, I)P(\text{cook}|I) + P(\text{chef}|\neg\text{cook}, I)P(\neg\text{cook}|I)$$

CN + ESPGAME Score



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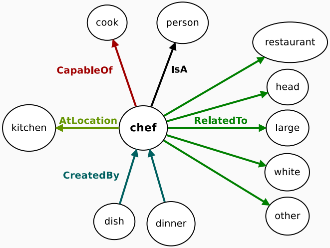
CN + ESPGAME Score



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$$P_c(\text{chef}|I) \approx P(\text{chef}|\text{cook}) \cdot 0.796 + P(\text{chef}|\neg\text{cook}) \cdot 0.204$$

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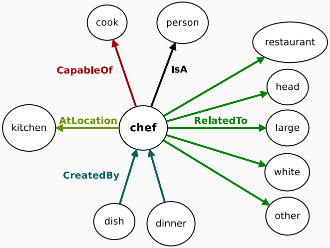

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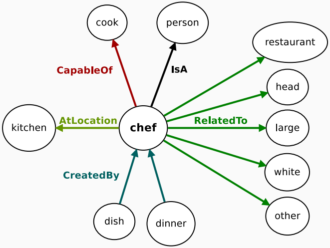
$$P_c(\text{chef}|I) \approx P(\text{chef}|\text{cook}) \cdot 0.796 + P(\text{chef}|\neg\text{cook}) \cdot 0.204$$
$$P_c(\text{chef}|I) \approx 0.1413 \cdot 0.796 + 0.0003 \cdot 0.204$$

CN + ESPGAME Score



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$$P_c(\text{chef}|I) \approx 0.1413 \cdot 0.796 + 0.0003 \cdot 0.204$$

$$P_c(\text{chef}|I) \approx 0.112$$

CN + ESPGAME Score

$$
\begin{aligned}
P_{\text{cook}}(\text{chef}|I) &\approx 0.1125 \\
P_{\text{kitchen}}(\text{chef}|I) &\approx 0.0549 \\
P_{\text{dish}}(\text{chef}|I) &\approx 0.0016 \\
P_{\text{person}}(\text{chef}|I) &\approx 0.0011 \\
P_{\text{dinner}}(\text{chef}|I) &\approx 0.0011 \\
P_{\text{head}}(\text{chef}|I) &\approx 0.0009 \\
P_{\text{other}}(\text{chef}|I) &\approx 0.0009 \\
P_{\text{white}}(\text{chef}|I) &\approx 0.0006
\end{aligned}
$$

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P_{\text{other}}(\text{chef}|I) &\approx 0.0009\\
P_{\text{white}}(\text{chef}|I) &\approx 0.0006
\end{aligned}
$$

$$
\begin{aligned}
\text{CNE}_{\text{MIN}}(\text{chef}) &= 0.0006\\
\text{CNE}_{\text{AVG}}(\text{chef}) &= 0.0217\\
\text{CNE}_{\text{MAX}}(\text{chef}) &= 0.1125
\end{aligned}
$$

CN + ESPGAME Score

Database ⊂ COCO 5K	r@1	r@5	r@10	median rank	mean rank
Baseline					
MIL	13.2	33.4	45.2	13	82.2
CN + ESPGAME					
CNE_{MIN}	14.3	34.6	46.6	**12**	68.3
CNE_{AVG}	**14.6**	35.6	48.0	**12**	61.2
CNE_{MAX}	14.3	**35.9**	**48.2**	**12**	**60.6**
CN Gain	**1.4%**	**2.5%**	**3.0%**	**1**	**21.6**

CN + ESPGAME Score

$t =$ "a woman in a chef coat holding bread loaves"

1

2

3

4

...

512

CN + ESPGAME Score

$t =$ "a woman in a chef coat holding bread loaves"

    ... 

1 2 3 4 **512**

    ... 

1 2 3 4 **35**

CN + ESPGAME Score

$t =$ "those bagels are plain with nothing on them"


1


2


3


4

...


360

CN + ESPGAME Score

t = "those bagels are plain with nothing on them"


1

2

3

4
...

360


1

2

3

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...

2

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Contribution

Results and Discussion

Database COCO 5K	r@1	r@5	r@10	median rank	mean rank
NeuralTalk (Vinyals et al., 2015)	6.9	22.1	33.6	22	72.2
GMM+HGLMM (Klein et al., 2015)	10.8	28.3	40.1	17	49.3
BRNN (Karpathy and Fei-Fei, 2015)	10.7	29.6	42.2	14	–
MIL (our baseline)	15.7	37.8	50.5	10	53.6
$\mathbf{CNE}_{\mathbf{MAX}}$ (our method)	16.2	39.1	51.9	10	44.4
LVQ (Lin and Parikh, 2016)	16.7	40.5	53.8	–	–
OE (Vendrov et al., 2016)	18.0	–	57.6	7.0	35.9
	higher is better			lower is better	

Results and Discussion

Database $\subset$ COCO 5K	r@1	r@5	r@10	median rank	mean rank
MIL (our baseline)	13.2	33.4	45.2	13	82.2
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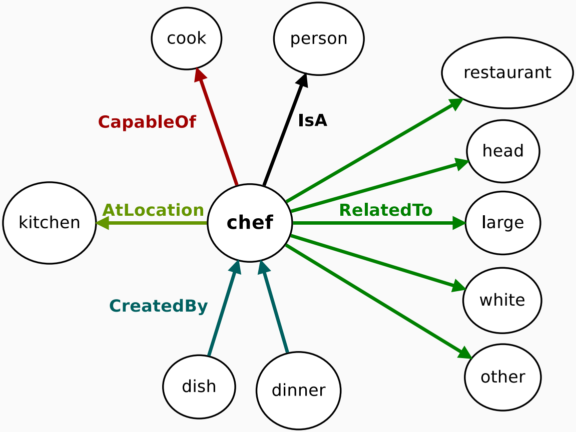

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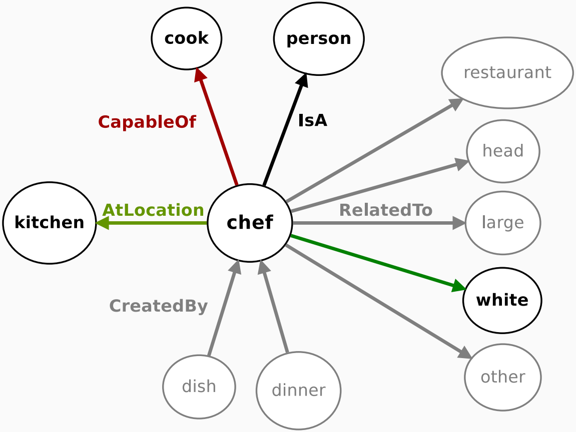

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We can exploit commonsense ontologies in Computer Vision

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CN for image retrieval... sucks!

CN + ESPGAME for image retrieval... works!

Contribution

We can exploit commonsense ontologies in Computer Vision, but this knowledge must be filtered in a meaningful way (e.g. using ESPGAME).

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Conclusion

Our code: https://bitbucket.org/RToroIcarte/cn-detectors

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If you want to share ideas about commonsense knowledge in Computer Vision, please come to check my poster :)

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Thank you!

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