A Poodle or a Dog ?

Evaluating Automatic Image Annotation Using Human Descriptions at Different Levels of Granularity

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Main Idea

Label this picture with an object name

Main Idea

Label this picture with an object name

Dog Poodle Mammal

Animal Pet Canine

Main Idea

System 1

1. Dog
2. Sheep
3. Sandal
4. Chihuahua
5. Footwear
6. Grass

...

Annotation: Dog

System 2

1. Poodle
2. Footwear
3. Grass
4. Horse
5. Dog
6. Cat

...

1. {Dog, Chihuahua, Poodle}
2. {Sheep}
3. {Footwear, Sandal, Flip-flop}
4. {Grass, Pasture}
5. {Horse, Pony}

...

1. {Dog, Chihuahua, Poodle}
2. {Footwear, Sandal, Flip-flop}
3. {Grass, Pasture}
4. {Horse, Pony}
5. {Cat, Kitty}

...

‘Granularity aware’ groupings

- Group semantically related concepts
- *Across* varying levels of granularity
- Used at **evaluation** time
  - Initial rankings are altered in a manner that gives different insights

Related Work

- Basic-level categories (Biederman 1995)
- Differences in abstraction level when labelling groups of images vs. describing individual images (Rorissa 2008)
- Classifiers decide the best level of abstraction (Deng et al 2012)
- Learn most ‘natural’ basic-level category from text corpora (Ordonez et al 2013)
- We focus on *evaluating* systems across *multiple* levels of granularity

Method Outline

Cat
Dog
Footwear
Grass
Poodle
Sandal
…

Semantic Grouping

{Cat}
{Dog, Poodle}
{Footwear, Sandal}
{Grass, Pasture}
{Horse, Pony}
…

A ***dog*** is running away with a ***sandal*** in its mouth.
A large white ***poodle*** is walking on the grass carrying a ***sandal***.
A large white ***poodle*** running along with a pink ***flip flop*** in its mouth.
A white ***dog*** carries a pink ***flip-flop*** through the green yard.
Large white ***poodle*** carrying a pink ***flip flop*** outside.

Human Descriptions to 'Gold Standard'

{Dog, Poodle}
{Footwear, Sandal}

1. Poodle
2. Footwear
3. Grass
4. Horse
5. Dog

…

Reranking Classifier Output

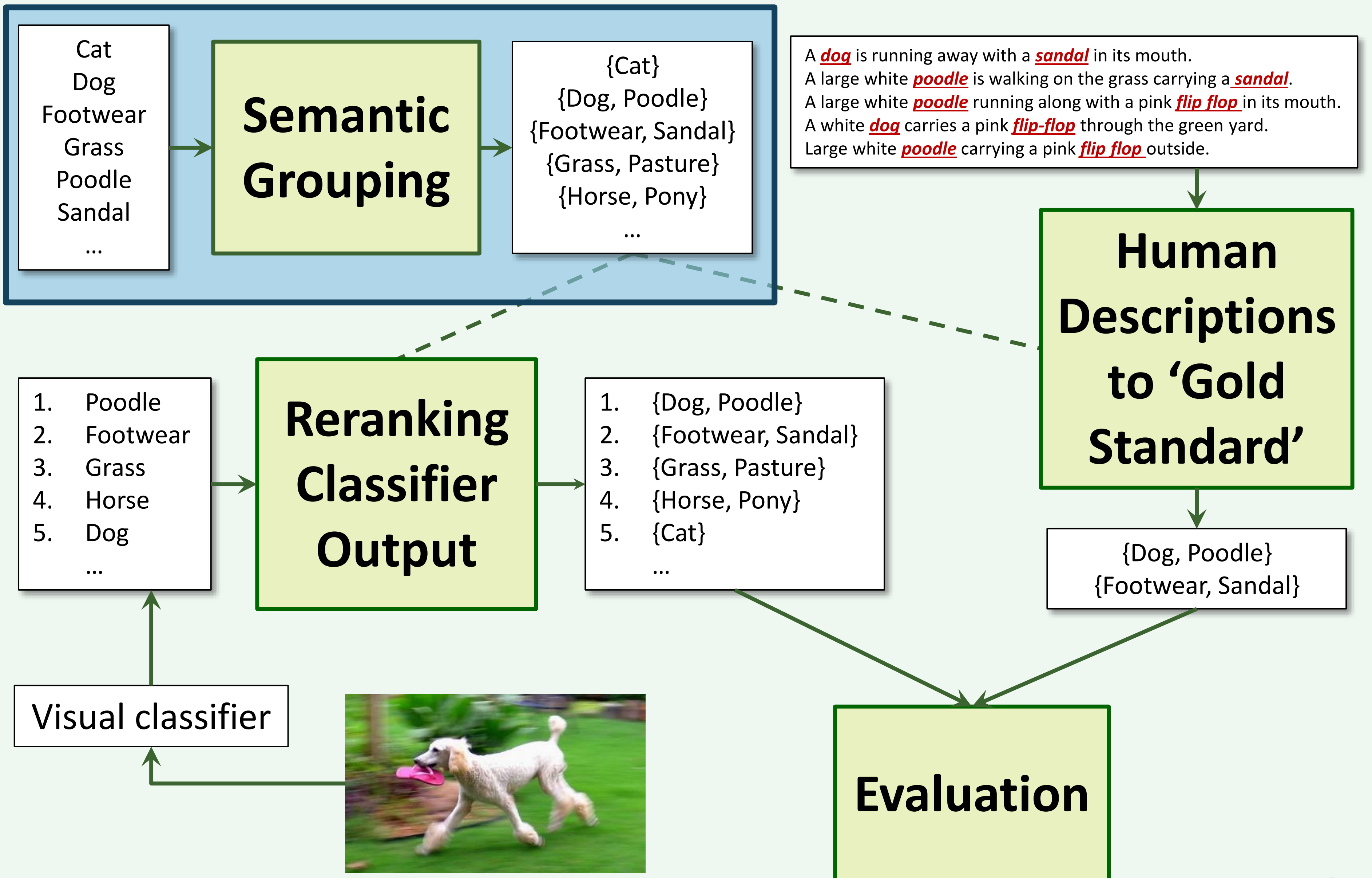
1. {Dog, Poodle}
2. {Footwear, Sandal}
3. {Grass, Pasture}
4. {Horse, Pony}
5. {Cat}

…

Visual classifier

Evaluation

Semantic Grouping



Semantic Grouping

Translation function from concept *v* to basic-level concepts (Ordonez et al. 2013)

ϕ	Concept	ψ
$\phi(being) = ln(235150)$	**being**	$\psi(being, poodle) = 3$
$\phi(animal) = ln(325501)$	**animal**	$\psi(animal, poodle) = 2$
$\phi(dog) = ln(406321)$	**dog**	$\psi(dog, poodle) = 1$
$\phi(poodle) = ln(6448)$	**poodle**	$\psi(poodle, poodle) = 0$

$$\tau(v, \lambda) = \arg\max_{w \in \Pi(v)} \left[\lambda\, \phi(w) - (1 - \lambda)\, \psi(w, v) \right]$$

hypernyms of *v*

'naturalness' (YFCC100M dataset)

semantic distance (WordNet)

Semantic Grouping

Group all concepts *v* translating to the same hypernym *w*

dog

$$\tau(\text{chihuahua}, \lambda) = \text{dog}$$
$$\tau(\text{dog}, \lambda) = \text{dog}$$
$$\tau(\text{poodle}, \lambda) = \text{dog}$$
$$\tau(\text{terrier}, \lambda) = \text{dog}$$

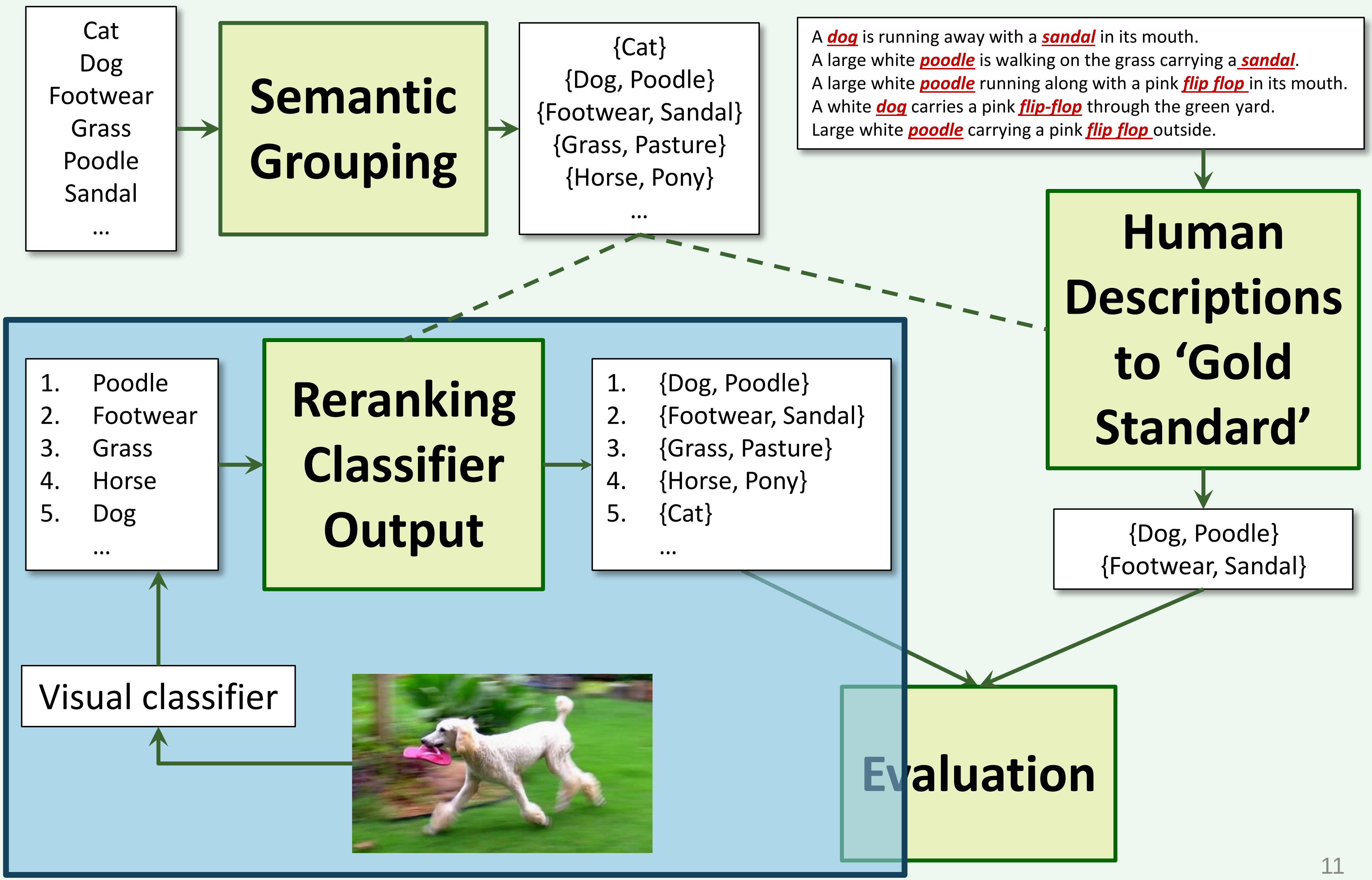
footwear

$$\tau(\text{footwear}, \lambda) = \text{footwear}$$
$$\tau(\text{sandal}, \lambda) = \text{footwear}$$

animal

$$\tau(\text{animal}, \lambda) = \text{animal}$$
$$\tau(\text{creature}, \lambda) = \text{animal}$$
$$\tau(\text{mussel}, \lambda) = \text{animal}$$

Reranking Classifier Output



Reranking Classifier Output

$\boldsymbol{\lambda = 0.5}$

Visual classifiers

1. poodle (0.92)
2. footwear (0.81)
3. grass (0.80)
4. horse (0.75)
5. dog (0.74)

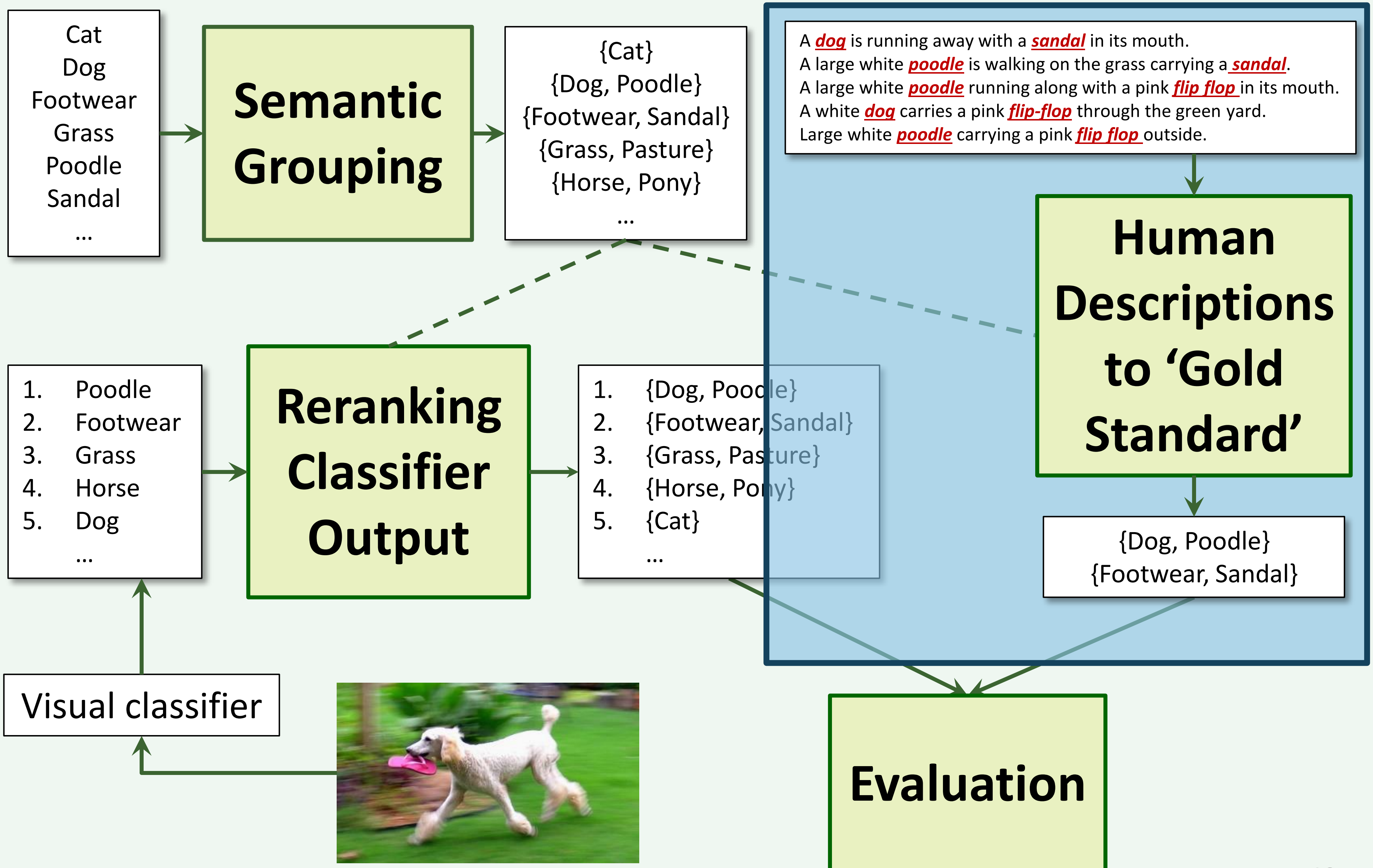
…

dog: {chihuahua, dog, poodle}
footwear: {footwear, sandal}
frisbee: {frisbee}
horse: {cob, horse, pony}
pasture: {pasture, grass}
animal: {animal, creature, mussel}
…

1. ***dog***: {chihuahua, dog, poodle} (0.92)
2. ***footwear***: {footwear, sandal} (0.81)
3. ***pasture***: {pasture, grass} (0.80)
4. ***horse***: {cob, horse, pony} (0.75)
5. ***frisbee***: {frisbee} (0.69)

…

Human Descriptions to 'Gold Standard'



Human Descriptions to 'Gold Standard'

- Flickr8k Dataset (Hodosh et al. 2013)
  - 8,091 images, 5 descriptions each

A dog is running away with a sandal in its mouth.
A large white poodle is walking on the grass carrying a sandal.
A large white poodle running along with a pink flip flop in its mouth.
A white dog carries a pink flip-flop through the green yard.
Large white poodle carrying a pink flip flop outside.

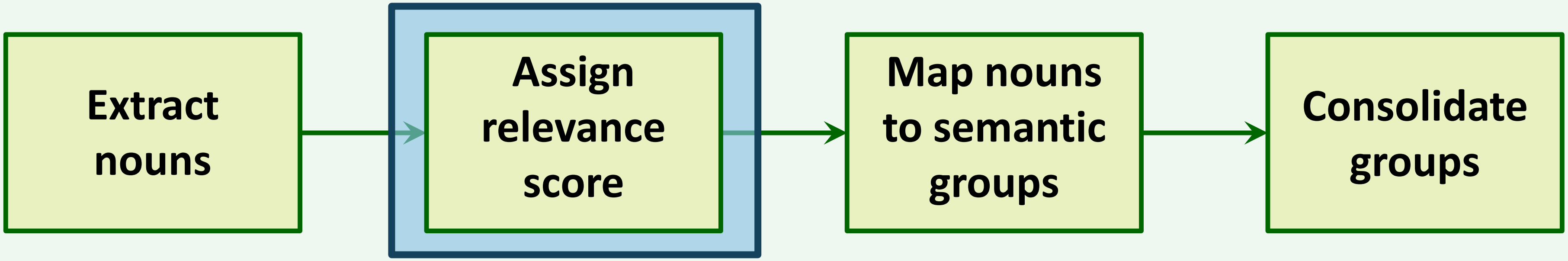
Human Descriptions to 'Gold Standard'

Extract nouns → **Assign relevance score** → **Map nouns to semantic groups** → **Consolidate groups**

A ***dog*** is running away with a ***sandal*** in its ***mouth***.
A large white ***poodle*** is walking on the ***grass*** carrying a ***sandal***.
A large white ***poodle*** running along with a pink ***flip flop*** in its ***mouth***.
A white ***dog*** carries a pink ***flip-flop*** through the green ***yard***.
Large white ***poodle*** carrying a pink ***flip flop*** outside.

dog **poodle** **sandal** **flip-flop** **grass** **yard** **mouth**

Human Descriptions to 'Gold Standard'



A ***dog*** is running away with a ***sandal*** in its ***mouth***.
A large white ***poodle*** is walking on the ***grass*** carrying a ***sandal***.
A large white ***poodle*** running along with a pink ***flip flop*** in its ***mouth***.
A white ***dog*** carries a pink ***flip-flop*** through the green ***yard***.
Large white ***poodle*** carrying a pink ***flip flop*** outside.

dog	poodle	sandal	flip-flop	grass	yard	mouth
2	3	2	3	2	1	2

Human Descriptions to 'Gold Standard'

Extract nouns → Assign relevance score → **Map nouns to semantic groups** → Consolidate groups

A ***dog*** is running away with a ***sandal*** in its ***mouth***.
A large white ***poodle*** is walking on the ***grass*** carrying a ***sandal***.
A large white ***poodle*** running along with a pink ***flip flop*** in its ***mouth***.
A white ***dog*** carries a pink ***flip-flop*** through the green ***yard***.
Large white ***poodle*** carrying a pink ***flip flop*** outside.

dog	poodle	sandal	flip-flop	grass	yard	mouth
2	3	2	3	2	1	2
dog	*dog*	*footwear*	*footwear*	*pasture*	*yard*	*mouth*

Human Descriptions to 'Gold Standard'

Extract nouns → **Assign relevance score** → **Map nouns to semantic groups** → **Consolidate groups**

A ***dog*** is running away with a ***sandal*** in its ***mouth***.
A large white ***poodle*** is walking on the ***grass*** carrying a ***sandal***.
A large white ***poodle*** running along with a pink ***flip flop*** in its ***mouth***.
A white ***dog*** carries a pink ***flip-flop*** through the green ***yard***.
Large white ***poodle*** carrying a pink ***flip flop*** outside.

dog	poodle	sandal	flip-flop	grass	yard	mouth
2	3	2	3	2	1	2

dog	*footwear*	*pasture*	*yard*	*mouth*
3	*3*	*2*	*1*	*2*

Evaluation

Cat
Dog
Footwear
Grass
Poodle
Sandal
…

Semantic Grouping

{Cat}
{Dog, Poodle}
{Footwear, Sandal}
{Grass, Pasture}
{Horse, Pony}
…

A ***dog*** is running away with a ***sandal*** in its mouth.
A large white ***poodle*** is walking on the grass carrying a ***sandal***.
A large white ***poodle*** running along with a pink ***flip flop*** in its mouth.
A white ***dog*** carries a pink ***flip-flop*** through the green yard.
Large white ***poodle*** carrying a pink ***flip flop*** outside.

Human Descriptions to 'Gold Standard'

{Dog, Poodle}
{Footwear, Sandal}

1. Poodle
2. Footwear
3. Grass
4. Horse
5. Dog

…

Reranking Classifier Output

1. {Dog, Poodle}
2. {Footwear, Sandal}
3. {Grass, Pasture}
4. {Horse, Pony}
5. {Cat}

…

Visual classifier

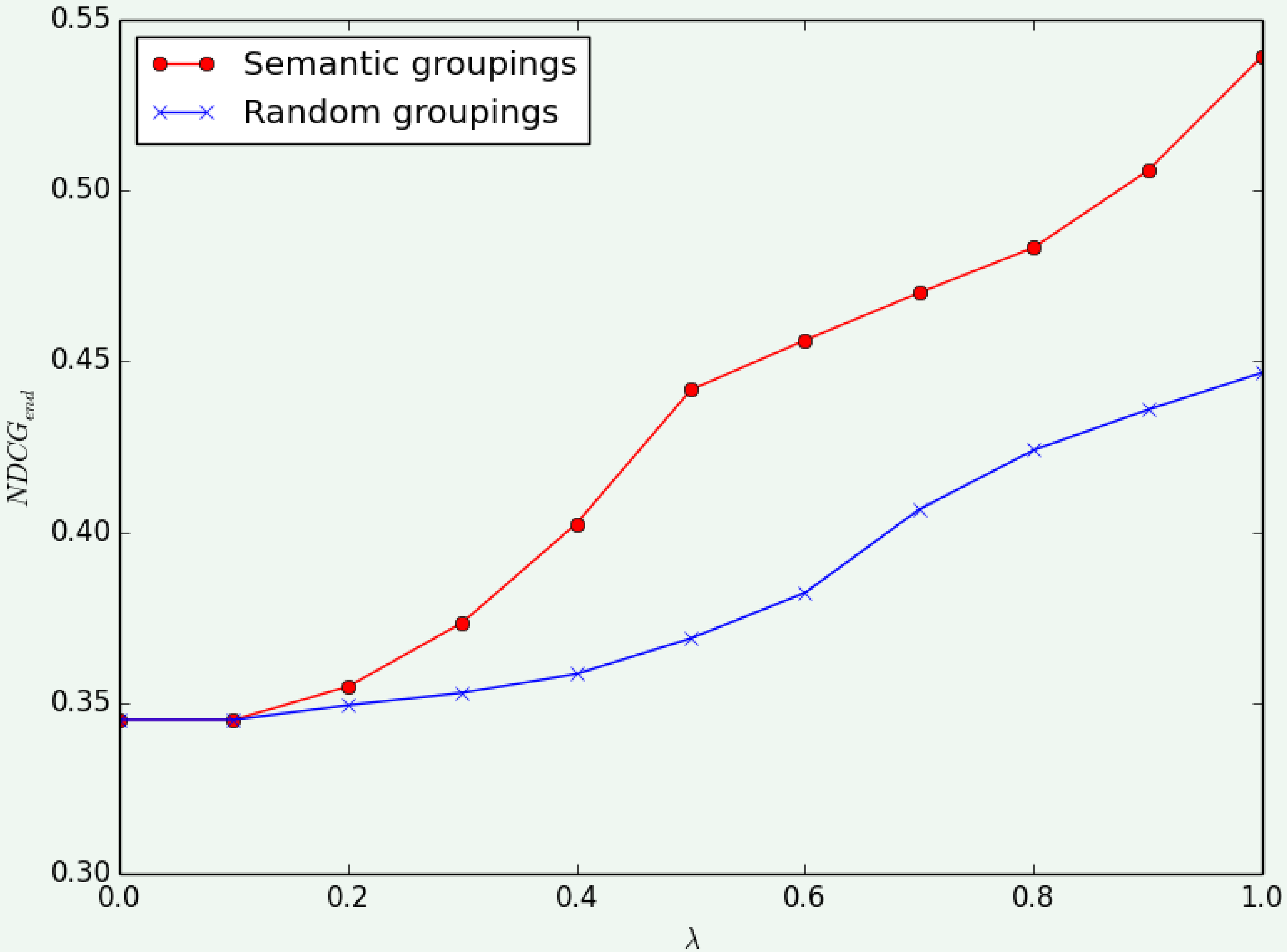
Evaluation

Evaluation Measure

- Normalized Discounted Cumulative Gain (NCDG)
  - Favours most relevant items first
  - Does not penalise irrelevant items
  - Normalised: between 0.0 to 1.0
    - Comparable across rankings with different no. of items

- Baseline: Concepts are grouped randomly

Results



Semantic groupings
Random groupings
0.55
0.50
0.45
0.40
0.35
0.30
0.0
0.2
0.4
0.6
0.8
1.0
$NDCG_{end}$
λ

Results

dog (5)
road (2)
sidewalk* (1)
street (1)

$\boldsymbol{\lambda = 0.0}$

beagle
boston_terrier
corgi
basset
hound
spaniel
border_collie
terrier
dachshund
pup
st_benard
bulldog
springer_spaniel
leash
kitten
pet
<u>dog</u>
sheepdog
penguin
<u>sidewalk</u>

sidewalk: **{pavement, sidewalk}**

Results

dog (5)
road (2)
sidewalk* (1)
street (1)

sidewalk: **{pavement, sidewalk}**

$\lambda = 0.0$	$\lambda = 0.3$
beagle	beagle
boston_terrier	boston_terrier
corgi	***dog***
basset	basset
hound	hound
spaniel	spaniel
border_collie	border_collie
terrier	terrier
dachshund	dachshund
pup	pup
st_benard	bulldog
bulldog	springer_spaniel
springer_spaniel	leash
leash	kitten
kitten	pet
pet	penguin
dog	***sidewalk***
sheepdog	doberman
penguin	collie
sidewalk	cat

Results

dog (5)
road (2)
sidewalk* (1)
street (1)

$\lambda = 0.3$	$\lambda = 0.5$
beagle	***dog***
boston_terrier	animal
dog	leash
basset	kitten
hound	pet
spaniel	penguin
border_collie	***sidewalk***
terrier	cat
dachshund	artifact
pup	person
bulldog	student
springer_spaniel	goat
leash	livestock
kitten	rabbit
pet	duck
penguin	baseball
sidewalk	chair
doberman	child
collie	frisbee
cat	spectator

sidewalk: **{pavement, sidewalk}**

Results

dog (5)
road (2)
sidewalk* (1)
street (1)

$\boldsymbol{\lambda = 0.5}$

<u>dog</u>
animal
leash
kitten
pet
penguin
<u>sidewalk</u>
cat
artifact
person
student
goat
livestock
rabbit
duck
baseball
chair
child
frisbee
spectator

$\boldsymbol{\lambda = 0.8}$

<u>dog</u>
animal
leash
being
bird
<u>sidewalk</u>
cat
artifact
student
baseball
chair
child
frisbee
ball
slope
equipment
fabric
rug
seat
support

sidewalk: **{pavement, sidewalk}**

Results

boat (4)
graham (1)
raceway* (1)
vessel* (1)

raceway: **{race, raceway}**
vessel: **{vessel, watercraft}**

$\lambda = 0.0$	$\lambda = 0.3$
motorboat	***boat***
speedboat	lifeguard
lifeguard	lifeboat
lifeboat	car
racer	***vessel***
vessel	sidecar
car	kayak
barge	tugboat
sidecar	paddle
kayak	dinghy
boat	motor
tugboat	ferry
paddle	glass
dinghy	preserver
motor	***raceway***
ferry	oar
bumper	airplane
preserver	vehicle
raceway	raft
oar	hatchback

Results

boat (4)
graham (1)
raceway* (1)
vessel* (1)

raceway: **{race, raceway}**
vessel: **{vessel, watercraft}**

$\lambda = 0.3$	$\lambda = 0.5$
boat	***boat***
lifeguard	lifeguard
lifeboat	car
car	***vessel***
vessel	sidecar
sidecar	kayak
kayak	tugboat
tugboat	paddle
paddle	motor
dinghy	glass
motor	equipment
ferry	***raceway***
glass	oar
preserver	airplane
raceway	vehicle
oar	raft
airplane	hatchback
vehicle	device
raft	screen
hatchback	field

Results

***boat* (4)**
***graham* (1)**
***raceway* (1)**
<u>*vehicle*</u> *(1)*

vehicle: **{buggy, bulldozer, camper, carriage, cart, …, sailboat, …, vehicle, vessel, wagon, watercraft, wheelbarrow, yacht}**

$\lambda = 0.5$

<u>boat</u>
lifeguard
car
<u>vessel</u>
sidecar
kayak
tugboat
paddle
motor
glass
equipment
<u>raceway</u>
oar
airplane
vehicle
raft
hatchback
device
screen
field

$\lambda = 0.8$

<u>boat</u>
being
car
<u>vehicle</u>
artifact
tugboat
paddle
motor
glass
equipment
<u>raceway</u>
airplane
raft
structure
device
screen
field
wrapping
brush
pop

Discussion

- We proposed grouping semantically related concepts *across* different levels of granularity
- Semantic groups are used to alter visual classifier rankings, provides different insights
- Human-centric evaluation with descriptions
- Trade-off between flexibility vs. informativeness
- Future work:
  - Different methods of grouping concepts
  - Incorporate visual classifiers for grouping & reranking

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