



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

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Label this picture with an object name

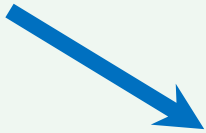
Dog Poodle Mammal
Animal Pet Canine

Main Idea

System 1

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

...



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

...



Annotation: Dog

System 2

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

...



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

...

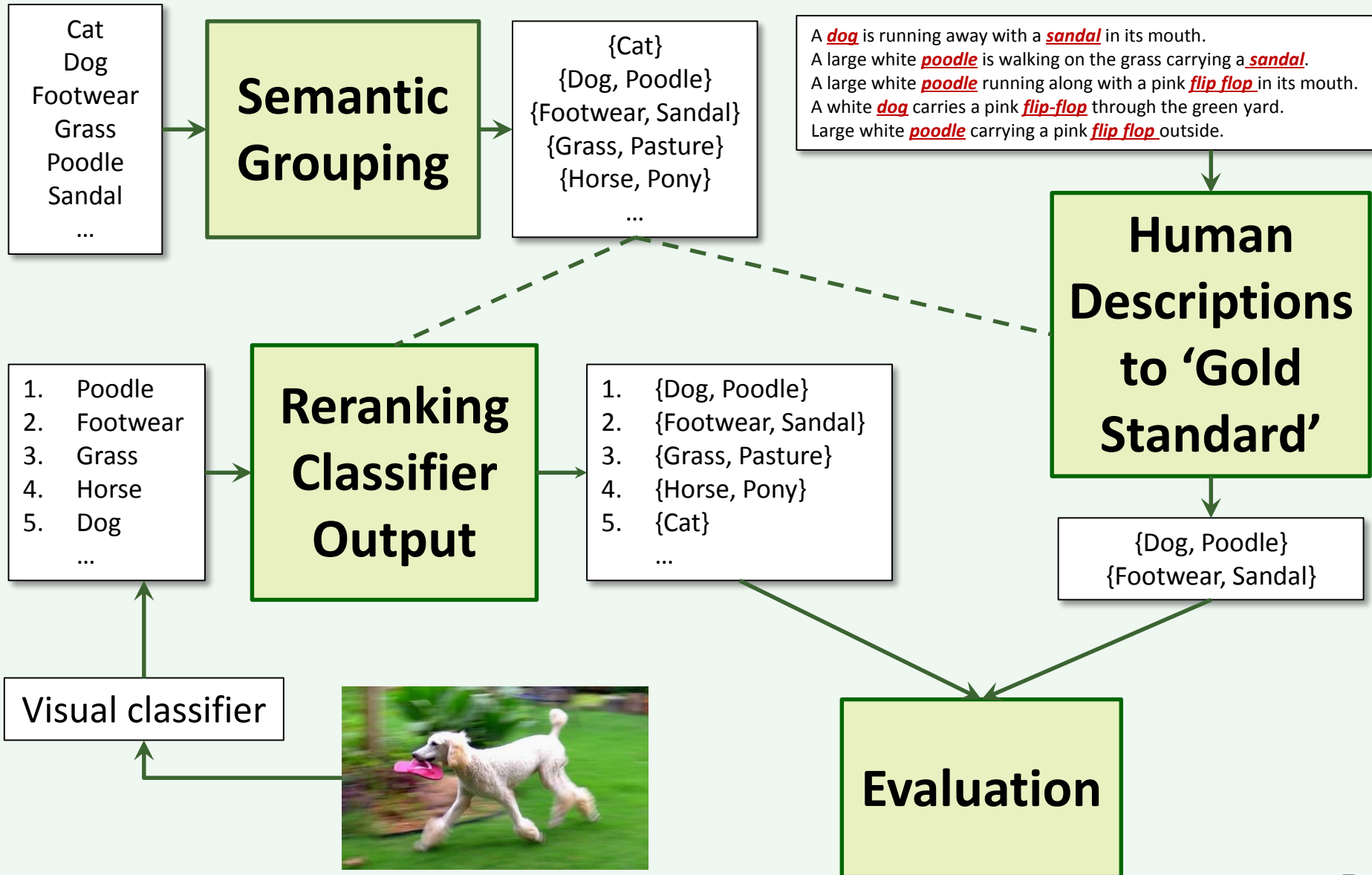
'Granularity aware' groupings

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

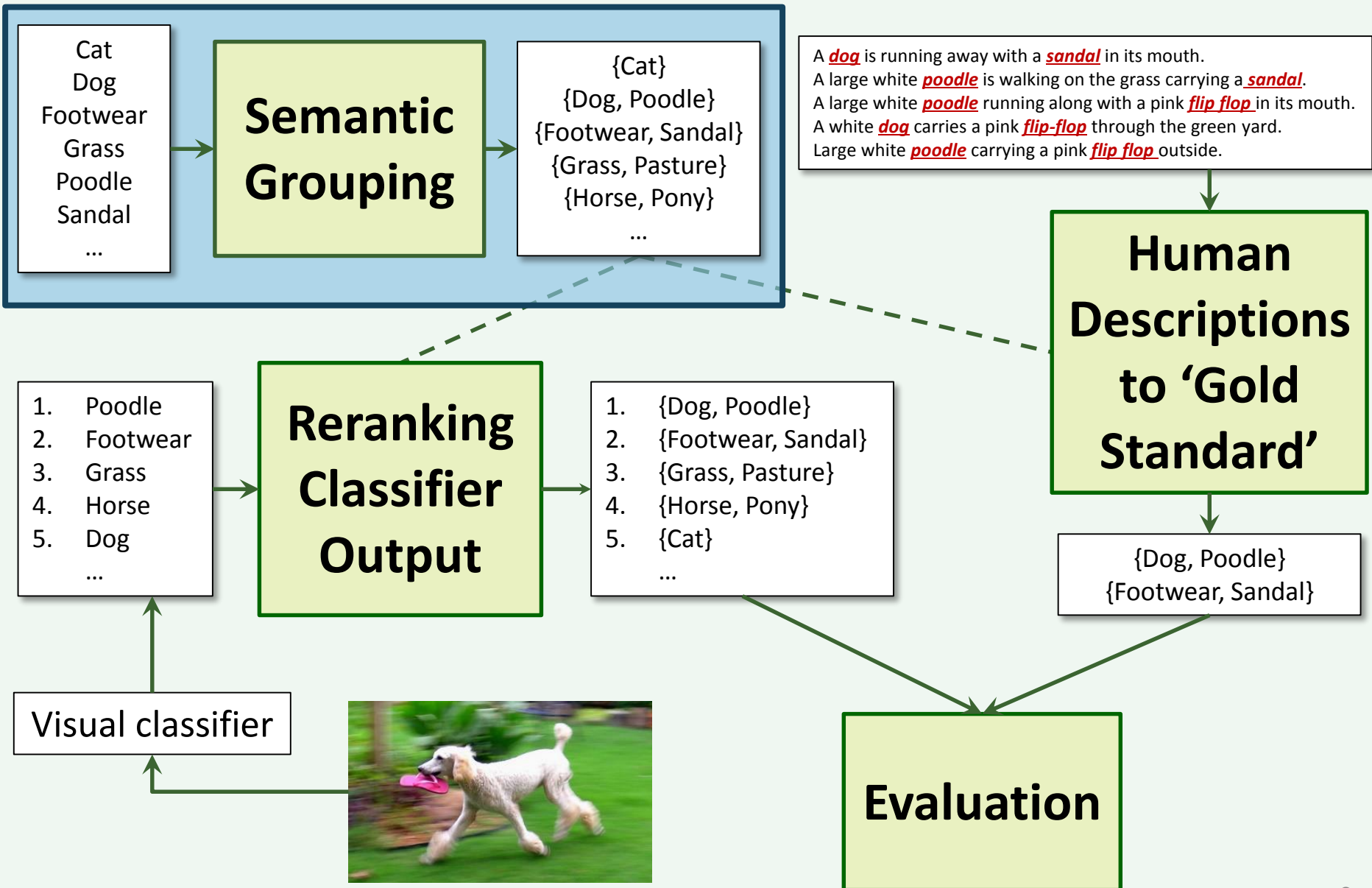
Related Work

- 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

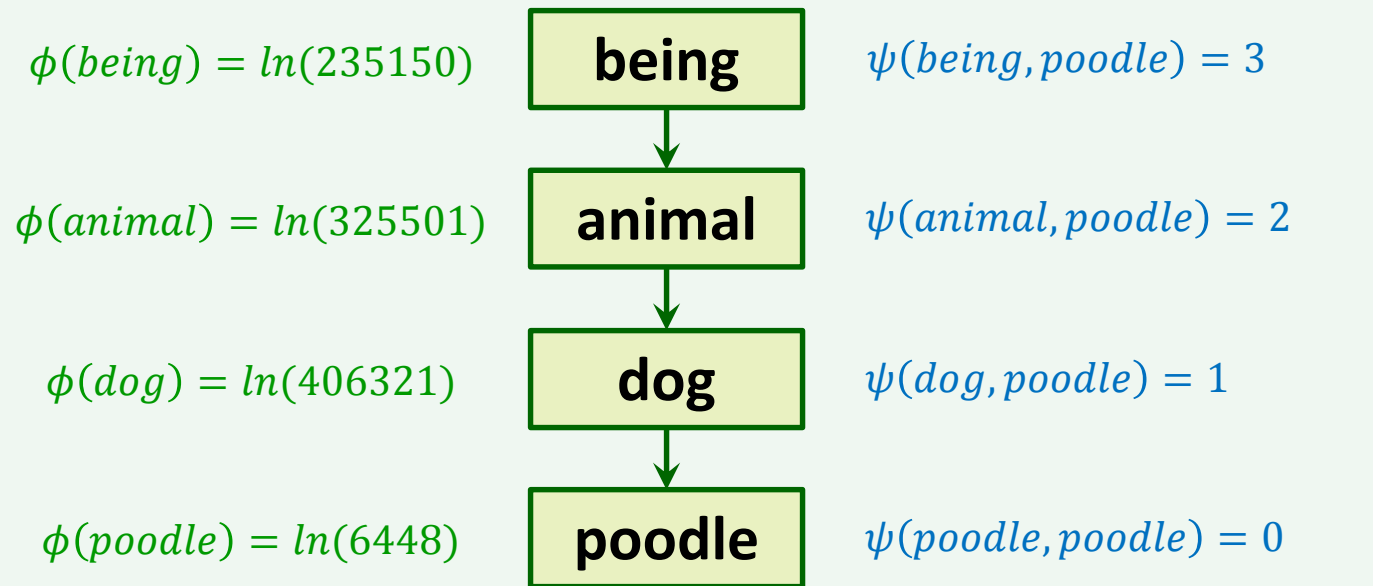


Semantic Grouping



Semantic Grouping

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



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

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

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

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

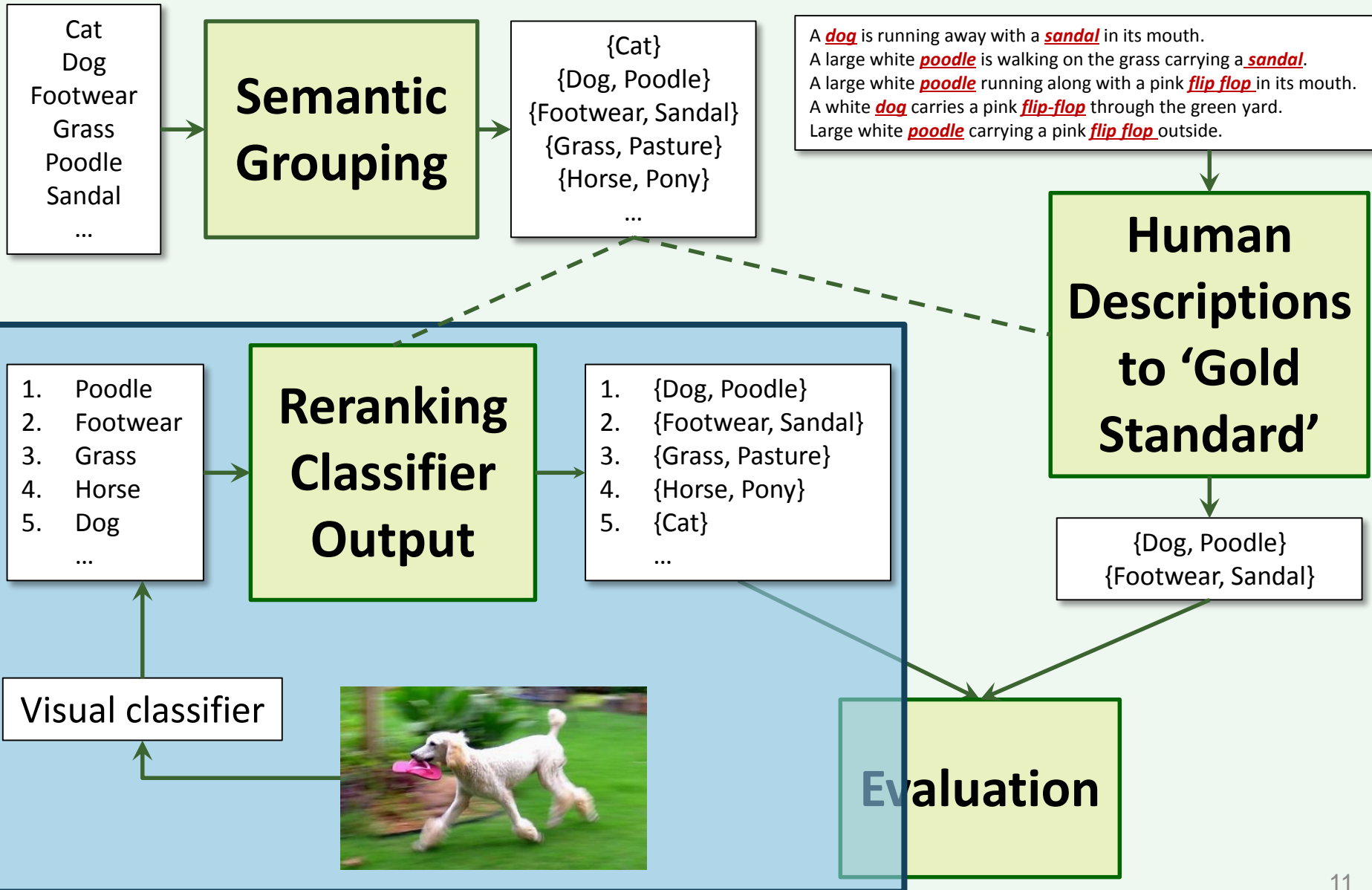
animal

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

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

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

Reranking Classifier Output



Reranking Classifier Output

$$\lambda = 0.5$$



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'

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'

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}
...

{Dog, Poodle}
{Footwear, Sandal}

Visual classifier



Evaluation

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.

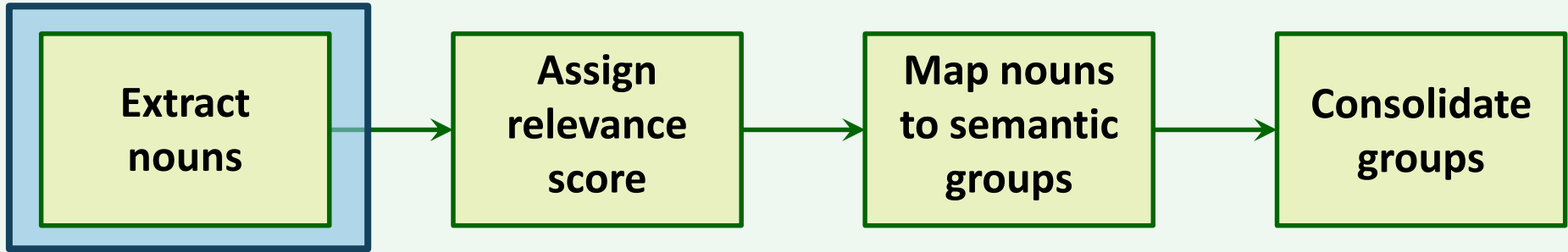
A large white poodle is walking on the grass carrying a sandal.

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'



A dog is running away with a sandal in its mouth.

A large white poodle is walking on the grass carrying a sandal.

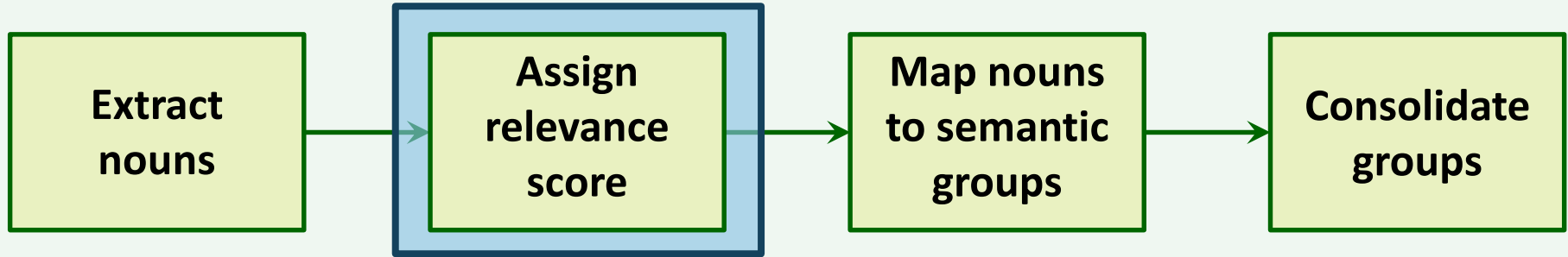
A large white poodle running along with a pink flip flop in its mouth.

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.

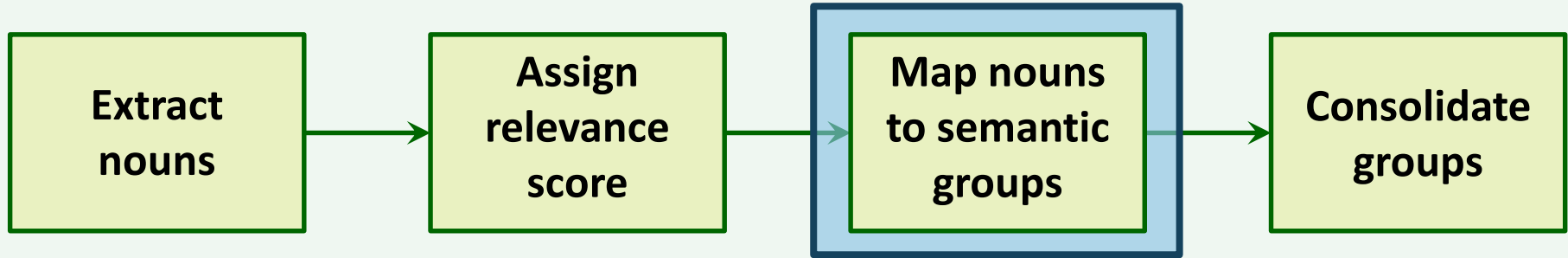
A large white poodle running along with a pink flip flop in its mouth.

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'



A dog is running away with a sandal in its mouth.

A large white poodle is walking on the grass carrying a sandal.

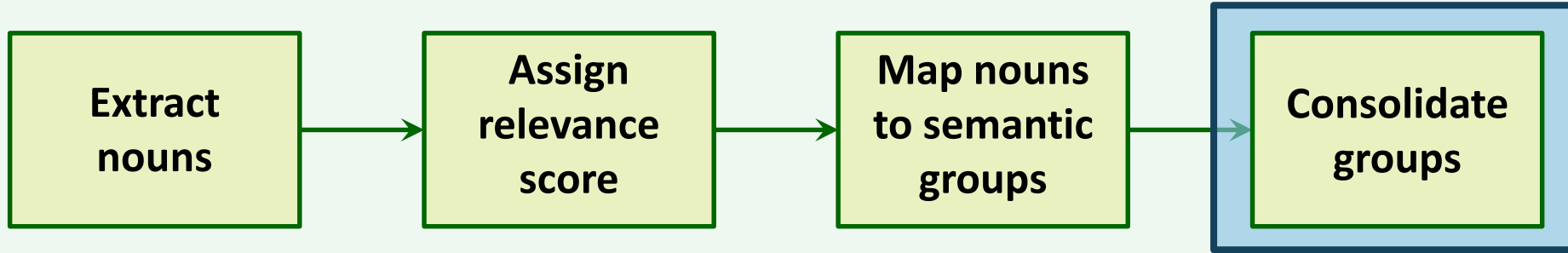
A large white poodle running along with a pink flip flop in its mouth.

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'



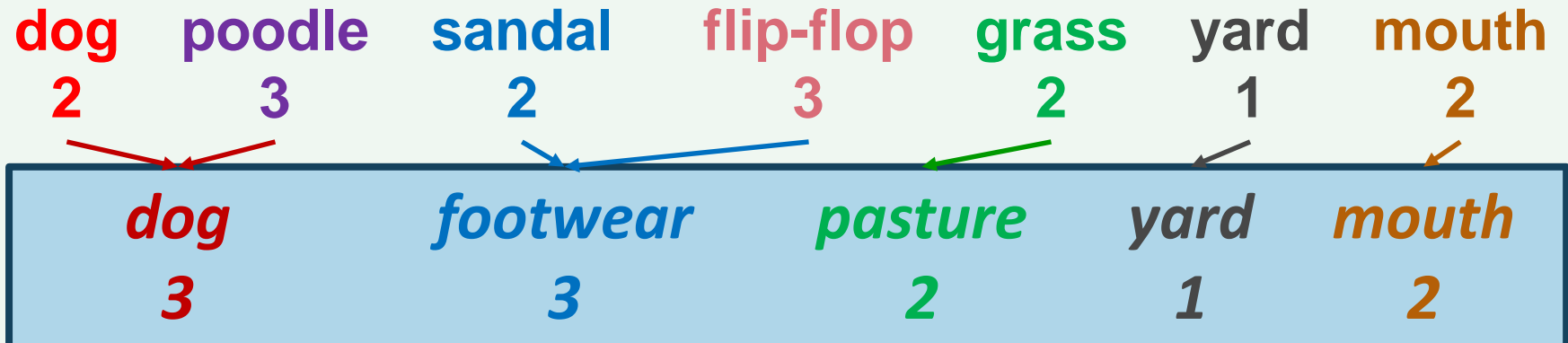
A dog is running away with a sandal in its mouth.

A large white poodle is walking on the grass carrying a sandal.

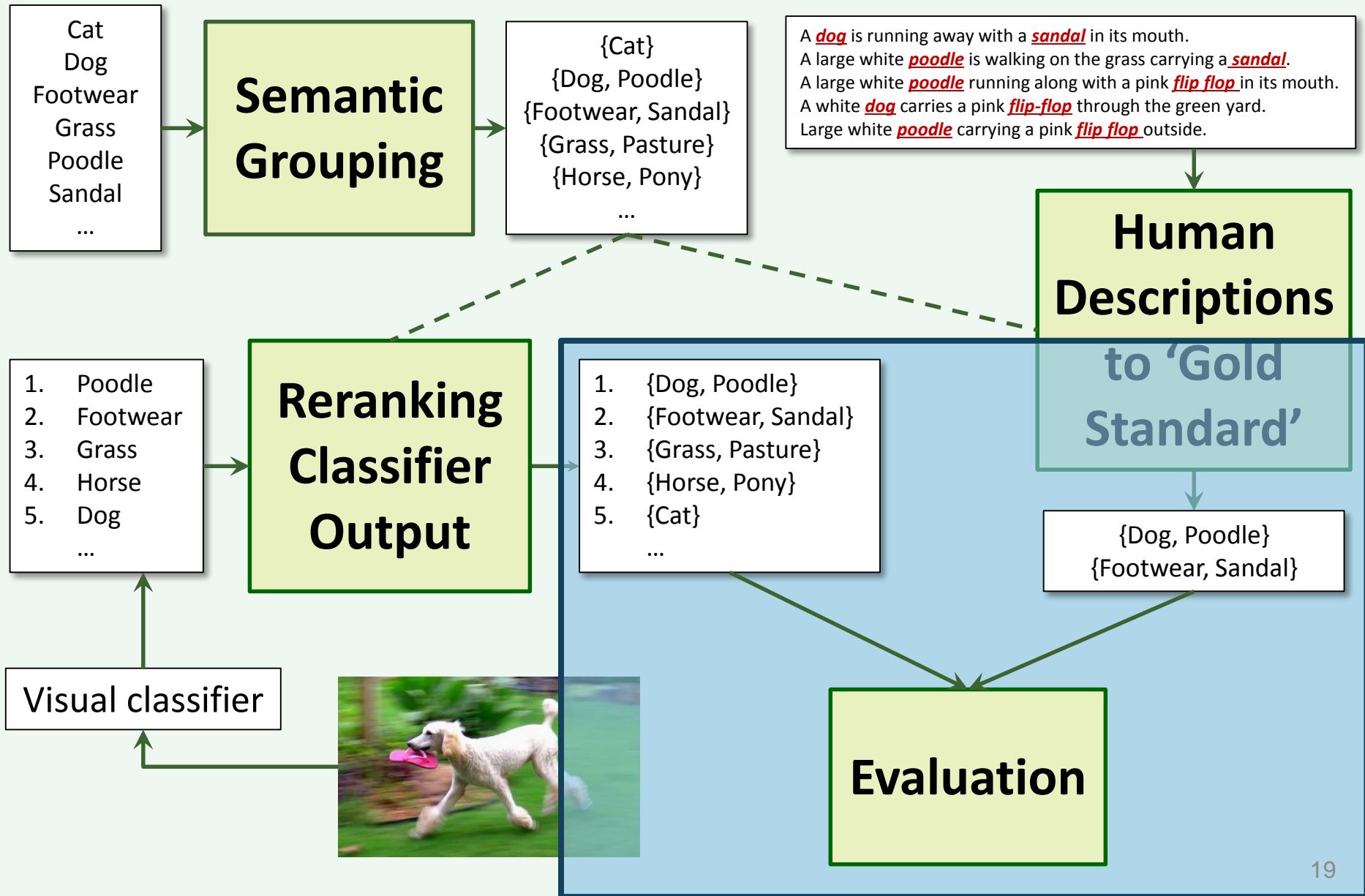
A large white poodle running along with a pink flip flop in its mouth.

A white dog carries a pink flip-flop through the green yard.

Large white poodle carrying a pink flip flop outside.



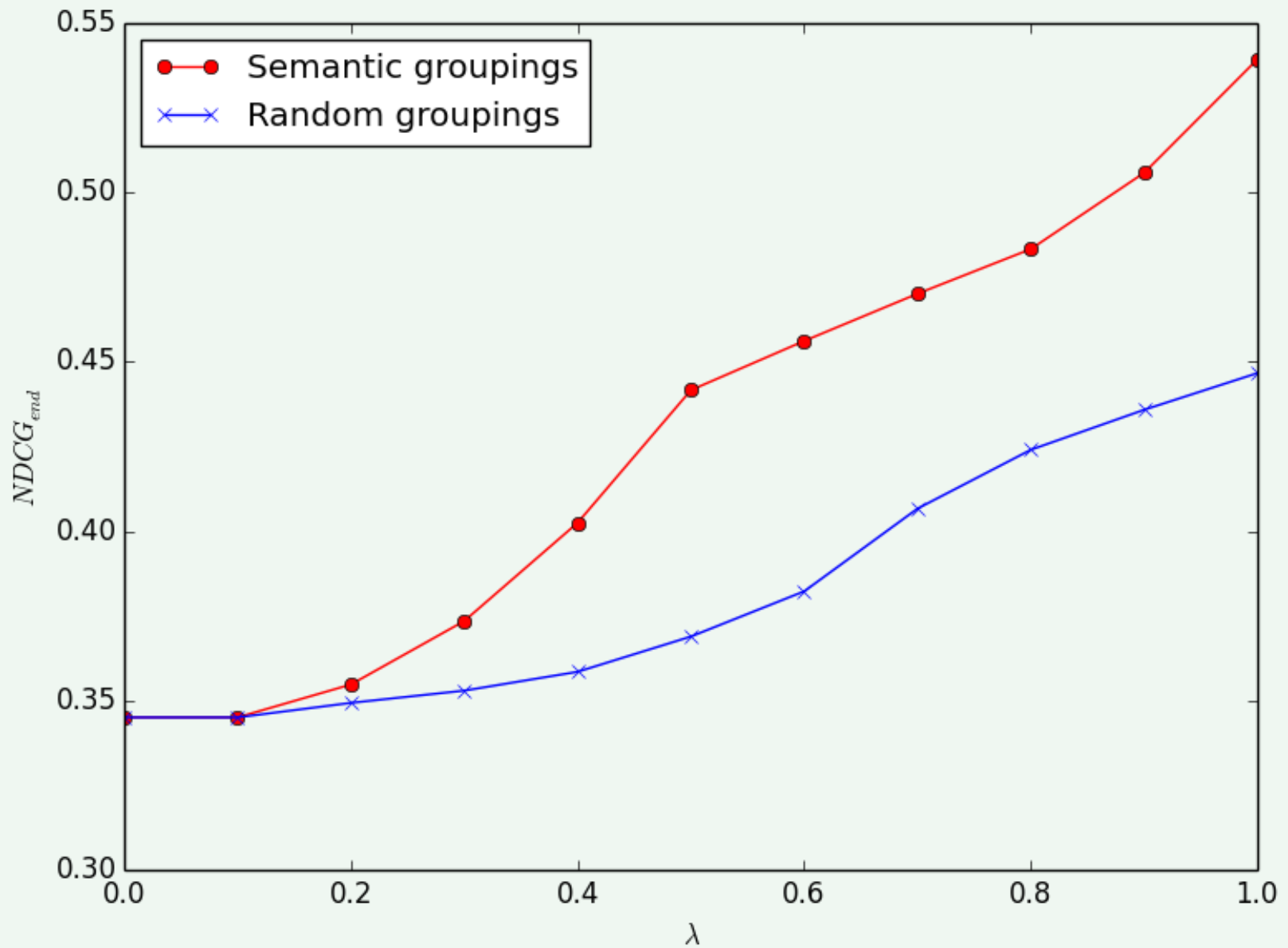
Evaluation



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



Results



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

sidewalk: {pavement, sidewalk}

$\lambda = 0.0$

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

Results



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

sidewalk: {pavement, sidewalk}

$\lambda = 0.0$

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

$\lambda = 0.3$

beagle
boston_terrier
dog
basset
hound
spaniel
border_collie
terrier
dachshund
pup
bulldog
springer_spaniel
leash
kitten
pet
penguin
sidewalk
doberman
collie
cat

Results



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

sidewalk: {pavement, sidewalk}

$\lambda = 0.3$

beagle
boston_terrier
dog
basset
hound
spaniel
border_collie
terrier
dachshund
pup
bulldog
springer_spaniel
leash
kitten
pet
penguin
sidewalk
doberman
collie
cat

$\lambda = 0.5$

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

Results



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

sidewalk: {pavement, sidewalk}

$\lambda = 0.5$

dog

animal

leash

kitten

pet

penguin

sidewalk

cat

artifact

person

student

goat

livestock

rabbit

duck

baseball

chair

child

frisbee

spectator

$\lambda = 0.8$

dog

animal

leash

being

bird

sidewalk

cat

artifact

student

baseball

chair

child

frisbee

ball

slope

equipment

fabric

rug

seat

support

Results



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

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

$\lambda = 0.0$

motorboat
speedboat
lifeguard
lifeboat
racer

vessel

car
barge
sidecar
kayak
boat
tugboat
paddle
dinghy
motor
ferry
bumper
preserver
raceway
oar

$\lambda = 0.3$

boat

lifeguard
lifeboat
car

vessel

sidecar
kayak
tugboat
paddle
dinghy
motor
ferry
glass
preserver
raceway
oar
airplane
vehicle
raft
hatchback

Results



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

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

$\lambda = 0.3$

boat
lifeguard
lifeboat
car
vessel
sidecar
kayak
tugboat
paddle
dinghy
motor
ferry
glass
preserver
raceway
oar
airplane
vehicle
raft
hatchback

$\lambda = 0.5$

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

Results



boat (4)
graham (1)
raceway (1)
vehicle (1)

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

$\lambda = 0.5$

boat

lifeguard

car

vessel

sidecar

kayak

tugboat

paddle

motor

glass

equipment

raceway

oar

airplane

vehicle

raft

hatchback

device

screen

field

$\lambda = 0.8$

boat

being

car

vehicle

artifact

tugboat

paddle

motor

glass

equipment

raceway

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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