

(Supplementary) What leads to generalization of object proposals?

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Paper ID 13

1 List of OIV4 classes

OIV4-Target50: *Book, Bookcase, Bull, Cabbage, Camera, Centipede, Coat, Coffee cup, Computer keyboard, Desk, Dog, Doughnut, Egg, Falcon, Flowerpot, Fork, Goldfish, Hippopotamus, Hot dog, House, Juice, Kitchen knife, Knife, Lavender, Missile, Mobile phone, Motorcycle, Mug, Orange, Palm tree, Penguin, Piano, Picture frame, Porch, Rabbit, Refrigerator, Remote control, Rifle, Seahorse, Skateboard, Strawberry, Sunglasses, Swimming pool, Sword, Tap, Tripod, Truck, Washing machine, Wine glass, Zebra*

OIV4-Source432: *Accordion, Adhesive tape, Airplane, Alarm clock, Alpaca, Ambulance, Ant, Antelope, Apple, Artichoke, Asparagus, Axe, Backpack, Bagel, Balance beam, Balloon, Banana, Banjo, Barge, Barrel, Baseball bat, Baseball glove, Bat, Bathroom cabinet, Bathtub, Beaker, Bee, Beehive, Beer, Bell pepper, Belt, Bench, Bicycle, Bicycle helmet, Bicycle wheel, Bidet, Billboard, Billiard table, Binoculars, Blender, Blue jay, Boot, Bottle, Bow and arrow, Bowl, Bowling equipment, Box, Boy, Brassiere, Bread, Briefcase, Broccoli, Bronze sculpture, Brown bear, Burrito, Bus, Bust, Butterfly, Cabinetry, Cake, Cake stand, Calculator, Camel, Canary, Candle, Candy, Cannon, Canoe, Cantaloupe, Carrot, Cart, Castle, Cat, Cat furniture, Caterpillar, Cattle, Ceiling fan, Cello, Chainsaw, Chair, Cheese, Cheetah, Chest of drawers, Chicken, Chopsticks, Christmas tree, Closet, Cocktail, Coconut, Coffee, Coffee table, Coffeemaker, Coin, Common fig, Computer monitor, Computer mouse, Convenience store, Cookie, Corded phone, Countertop, Cowboy hat, Crab, Cream, Cricket ball, Crocodile, Croissant, Crown, Crutch, Cucumber, Cupboard, Curtain, Cutting board, Dagger, Deer, Diaper, Dice, Digital clock, Dinosaur, Dog bed, Doll, Dolphin, Door, Door handle, Dragonfly, Drawer, Dress, Drill, Drinking straw, Drum, Duck, Dumbbell, Eagle, Earrings, Elephant, Envelope, Fedora, Filing cabinet, Fire hydrant, Fireplace, Flag, Flute, Flying disc, Food processor, Football, Football helmet, Fountain, Fox, French fries, Frog, Frying pan, Gas stove, Giraffe, Girl, Glasses, Glove, Goat, Goggles, Golf ball, Golf cart, Gondola, Goose, Grape, Grapefruit, Guacamole, Guitar, Hamburger, Hammer, Hamster, Handbag, Handgun, Harbor seal, Harp, Harpsichord, Headphones, Hedgehog, Helicopter, High heels, Hiking equipment, Honeycomb, Horn, Horse, Houseplant, Human arm, Human beard, Human body, Human ear, Human eye, Human face, Human foot, Human hair, Human hand, Human head, Human leg, Human mouth, Human*

nose, Ice cream, Infant bed, Ipod, Isopod, Jacket, Jacuzzi, Jaguar, Jeans, Jellyfish, Jet ski, Jug, Kangaroo, Kettle, Kitchen and dining room table, Kite, Koala, Ladder, Ladybug, Lamp, Lantern, Laptop, Lemon, Leopard, Lifejacket, Light bulb, Lighthouse, Lily, Limousine, Lion, Lipstick, Lizard, Lobster, Loveseat, Lynx, Magpie, Man, Mango, Maple, Mechanical fan, Microphone, Microwave oven, Milk, Miniskirt, Mirror, Mixer, Mixing bowl, Monkey, Mouse, Muffin, Mule, Mushroom, Musical keyboard, Nail, Necklace, Nightstand, Oboe, Office building, Organ, Ostrich, Otter, Oven, Owl, Oyster, Paddle, Pancake, Panda, Paper towel, Parachute, Parking meter, Parrot, Pasta, Peach, Pear, Pen, Pencil case, Perfume, Picnic basket, Pig, Pillow, Pineapple, Pitcher, Pizza, Plastic bag, Plate, Platter, Polar bear, Pomegranate, Popcorn, Porcupine, Poster, Potato, Power plugs and sockets, Pretzel, Printer, Pumpkin, Punching bag, Raccoon, Radish, Ratchet, Raven, Rays and skates, Red panda, Rhinoceros, Rocket, Roller skates, Rose, Rugby ball, Ruler, Salad, Salt and pepper shakers, Sandal, Saucer, Saxophone, Scale, Scarf, Scissors, Scoreboard, Scorpion, Sea lion, Sea turtle, Seafood, Seat belt, Segway, Serving tray, Sewing machine, Shark, Sheep, Shelf, Shirt, Shorts, Shotgun, Shower, Shrimp, Sink, Ski, Skull, Skyscraper, Slow cooker, Snail, Snake, Snowboard, Snowman, Snowmobile, Snowplow, Sock, Sofa bed, Sombrero, Sparrow, Spice rack, Spider, Spoon, Sports uniform, Squid, Squirrel, Stairs, Starfish, Stationary bicycle, Stool, Stop sign, Street light, Stretcher, Studio couch, Submarine sandwich, Suit, Suitcase, Sun hat, Sunflower, Surfboard, Sushi, Swan, Swim cap, Swimwear, Syringe, Table tennis racket, Tablet computer, Taco, Tank, Tart, Taxi, Tea, Teapot, Teddy bear, Television, Tennis ball, Tennis racket, Tent, Tiara, Tick, Tie, Tiger, Tin can, Tire, Toilet, Toilet paper, Tomato, Toothbrush, Tortoise, Towel, Tower, Traffic light, Train, Training bench, Treadmill, Tree house, Trombone, Trumpet, Turkey, Umbrella, Unicycle, Van, Vase, Vehicle registration plate, Violin, Volleyball, Waffle, Wall clock, Wardrobe, Waste container, Watch, Watermelon, Whale, Wheel, Wheelchair, Whisk, Whiteboard, Willow, Window, Window blind, Wine, Wine rack, Wok, Woman, Wood-burning stove, Woodpecker, Worm, Wrench, Zucchini

2 List of COCO classes

COCO-Target10: *apple, car, cat, clock, dining table, fire hydrant, giraffe, hair drier, handbag, truck*

COCO-Source70: *airplane, backpack, banana, baseball bat, baseball glove, bear, bed, bench, bicycle, bird, boat, book, bottle, bowl, broccoli, bus, cake, carrot, cell phone, chair, couch, cow, cup, dog, donut, elephant, fork, frisbee, horse, hot dog, keyboard, kite, knife, laptop, microwave, motorcycle, mouse, orange, oven, parking meter, person, pizza, potted plant, refrigerator, remote, sandwich, scissors, sheep, sink, skateboard, skis, snowboard, spoon, sports ball, stop sign, suitcase, surfboard, teddy bear, tennis racket, tie, toaster, toilet, toothbrush, traffic light, train, tv, umbrella, vase, wine glass, zebra*

3 Training weakly supervised model

We train a weakly supervised detection model based on Fast R-CNN [1], with the same method as used in YOLO9000[2]. During training, the Fast R-CNN model assigns scores to all the proposals in the image. We then choose the highest scoring proposal (from the top 100 proposals in the image) for each weakly labelled class in the image and use it as the psuedo ground-truth bounding box to perform back propagation. Additionally all proposals which have an overlap greater than 0.7 with this bounding box are also treated as psuedo ground-truth, while all bounding boxes with an overlap greater than 0.5 and less than 0.7 are not used in backpropagation. We train the model for 90000 iterations.

We use 500 proposals in each image for both training and evaluation. However, we only use the top 100 proposals when choosing psuedo ground-truth during training. This allows the model to choose positive bounding boxes from the most confident proposals in the image, while use other proposals as back-ground proposals for training the detection model.

4 Sufficiency of prototypical classes

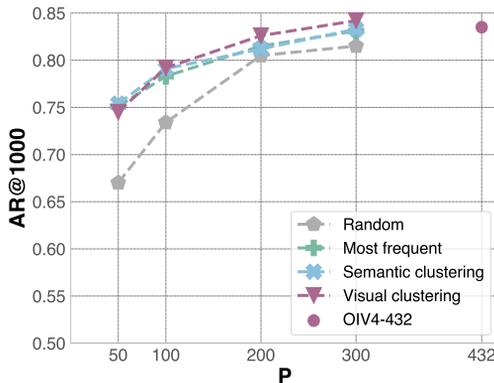


Fig. 1: Average recall AR@1000 for proposals obtained from models trained with varying number of prototypical classes chosen by different methods. We show the average recall on the OIV4-target dataset with 50 unseen classes. P denotes the number of prototypical classes. Higher value indicates higher sufficiency.

References

1. Girshick, R.: Fast R-CNN. In: ICCV (2015)
2. Redmon, J., Farhadi, A.: YOLO9000: better, faster, stronger. In: CVPR (2017)