

6.819 / 6.869: Advances in  
Computer Vision  
Project Overview

Project Website:

<http://6.869.csail.mit.edu/fa15/project.html>

Aude Oliva

# Projects (40%)

## Three Project Options

- 1) Summary of final project proposal (5%): 1 page (template) due **Tuesday Nov 10 on stellar**
  - Each person submits a file, but it can be the same within a team
- 2) Research component of final project (30%, template) and final presentation (5%).
  - Presentation (2-5 minutes each): Dec 3 (challenge), Dec 8 (projects)
  - Everybody in 6.868 presents.

# Summary of Project Proposal

- The same proposal can be submitted by all the team members (put the name of your teammates when submitting to stellar).
- The project proposal should be one page maximum this template:
- **What is the problem/question** that you will be investigating?
- **What are the most relevant readings?** (2-4 papers)
- **What data will you use?**
- **What method or algorithm will you use? For challenge/deep network: what changes do you plan to do?**
- **How will you evaluate your results?**  
Qualitatively, what kind of results do you expect (e.g. plots or figures)  
Quantitatively, what kind of analysis will you use to evaluate and/or compare your results (e.g. what performance metrics or statistical tests)?

# Project : A survey (individual) only for 6.819

- Select a topic (e.g. texture synthesis, face recognition, saliency models, computational neuroscience models of object recognition, machine learning techniques for vision, etc).
- Select 10-12 papers: **Project template to submit on stellar is the title of your survey and the reference list of 10-12 papers**
- Write a 2500 words survey article (a survey template will be given).
- You can opt for that option and change from a coding project to the survey, at any moment before Thanksgiving.
- Question: contact Aude (oliva@mit.edu)

# Project: Your own project

2-4 people

- **Applications/Models.** If you have access to a specific large image dataset (e.g. biology, engineering, physics, neuroscience) and a categorization task, you can apply models to this problem.
- From what you learn in class, you can choose a topic/question and propose an approach/model (including questions related to neuroscience).
- Submit also the proposal to stellar

# Project: Mini Places Challenge

## Goal: Build the best classifier you can for scenes



### Introduction

The goal of this challenge is to identify the scene category depicted in a photograph. The data for this task comes from the [Places2 dataset](#) which contains 10+ million images belonging to [400+ unique scene categories](#). Specifically, the challenge data will be divided into 8.1M images for training, 20k images for validation and 381k images for testing coming from 401 scene categories. Note that there is a non-uniform distribution of images per category for training, ranging from 4,000 to 30,000, mimicking a more natural frequency of occurrence of the scene.

For each image, algorithms will produce a list of at most 5 scene categories in descending order of confidence. The quality of a labeling will be evaluated based on the label that best matches the ground truth label for the image. The idea is to allow an algorithm to identify multiple scene categories in an image given that many environments have multi-labels (e.g. a bar can also be a restaurant) and that humans often describe a place using different words (e.g. forest path, forest, woods).

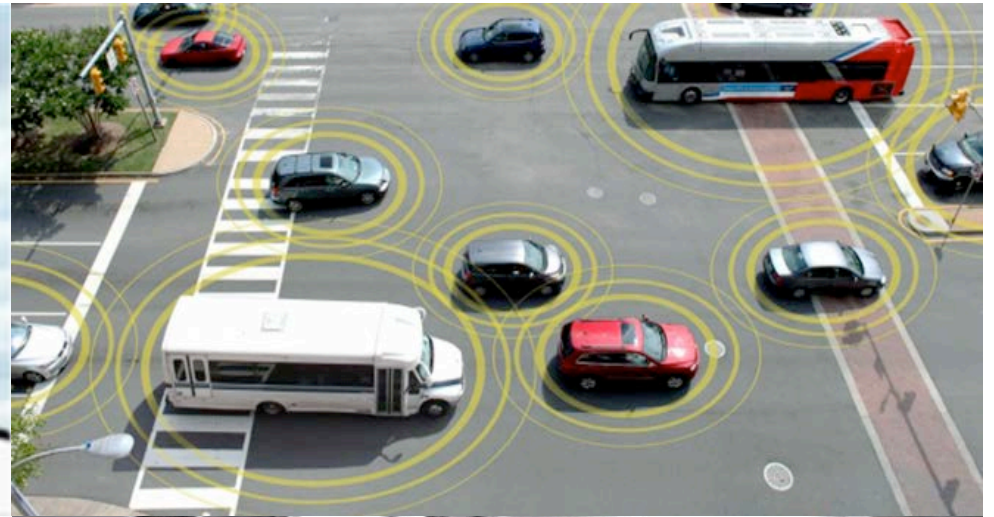
### Dates

- **August 15, 2015:** Development kit, data, and evaluation software made available
- **November 13, 2015, 5pm PST:** Submission deadline
- **December 10, 2015:** Challenge results released
- **December 17, 2015:** Winner(s) presents at ICCV 2015 Workshop













### Organizers

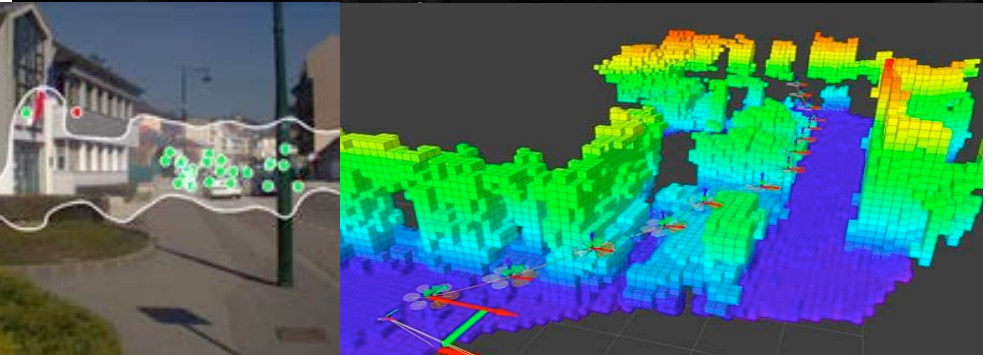
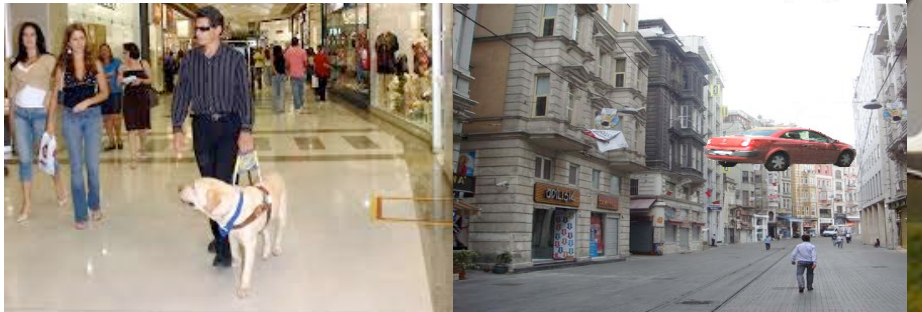
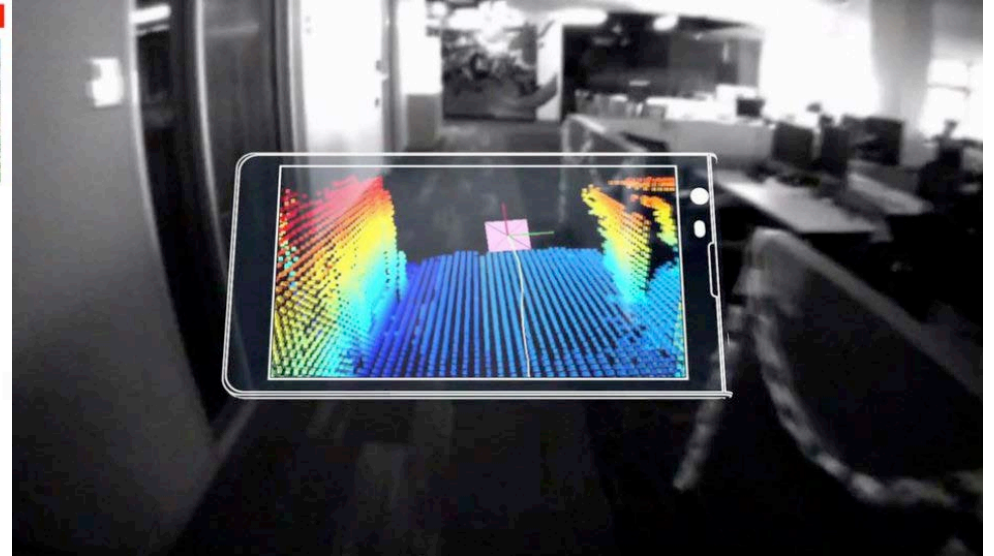
- [Aditya Khosla](#)
- [Bolei Zhou](#)
- [Agata Lapedriza](#)
- [Antonio Torralba](#)
- [Aude Oliva](#)



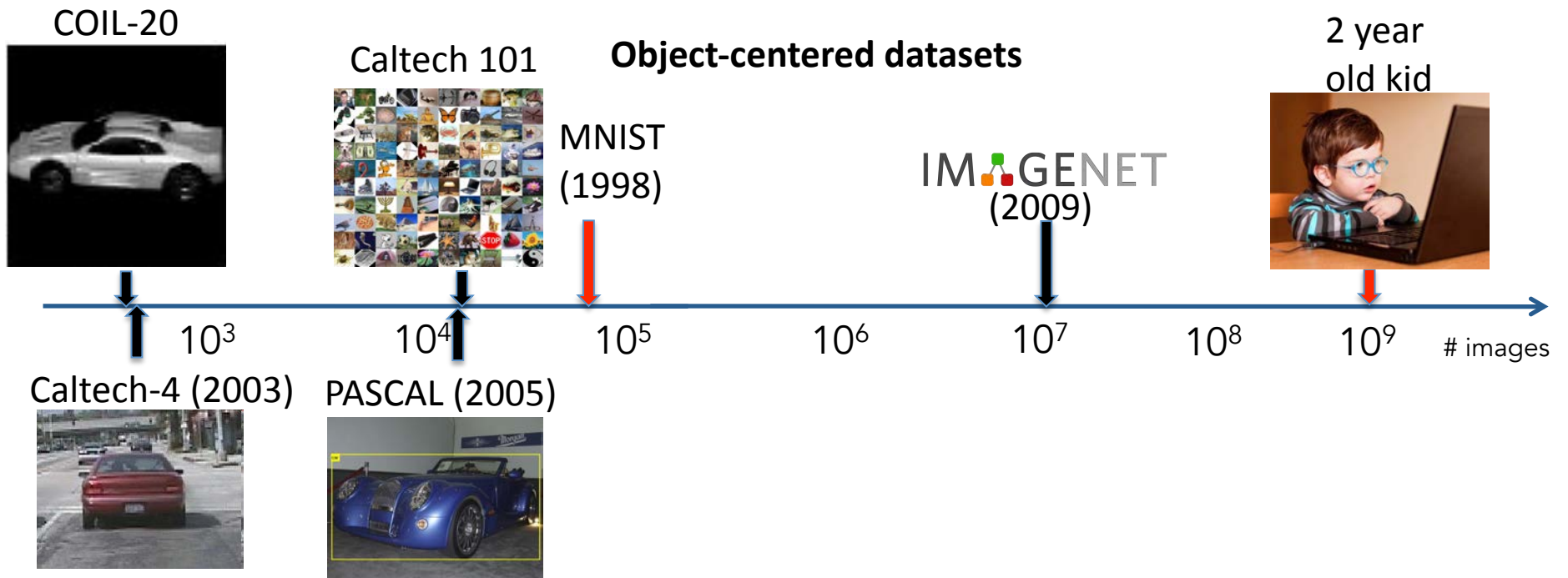


Describes without errors      Describes with minor errors      Somewhat related to the image      Unrelated to the image

 A person riding a motorcycle on a dirt road.	 Two dogs play in the grass.	 A skateboarder does a trick on a ramp.	 A dog is jumping to catch a frisbee.
 A group of young people playing a game of frisbee.	 Two hockey players are fighting over the puck.	 A little girl in a pink hat is blowing bubbles.	 A refrigerator filled with lots of food and drinks.
 A herd of elephants walking across a dry grass field.	 A close up of a cat laying on a couch.	 A red motorcycle parked on the side of the road.	 A yellow school bus parked in a parking lot.



# The evolution of vision databases





# IMAGENET Large Scale Visual Recognition Challenge

The Image Classification Challenge:  
1,000 object classes  
1,431,167 images

Top 5 categories



Output:  
Scale  
T-shirt  
Steel drum  
Drumstick  
Mud turtle



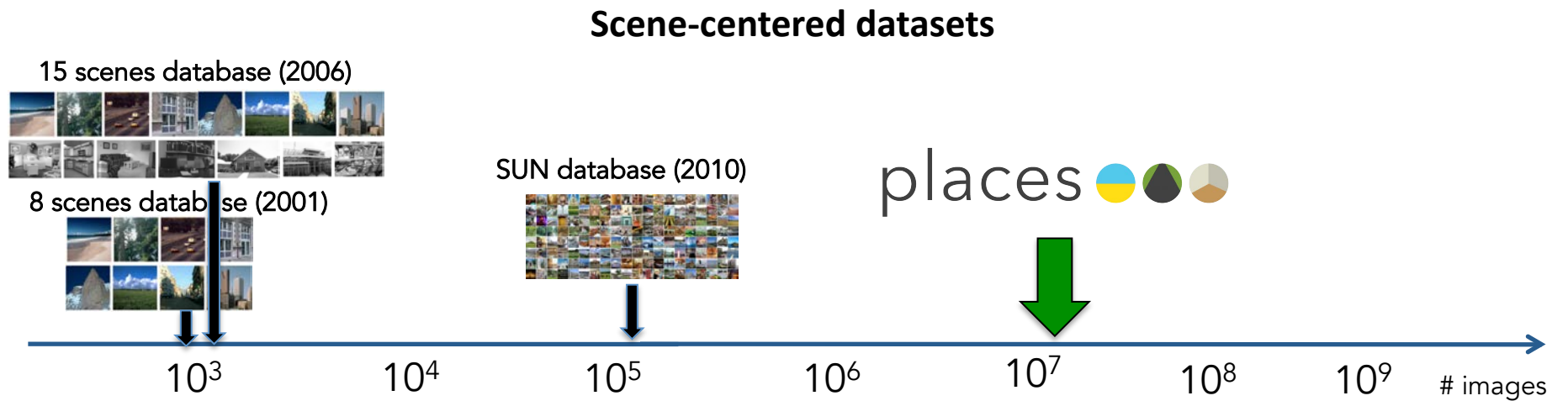
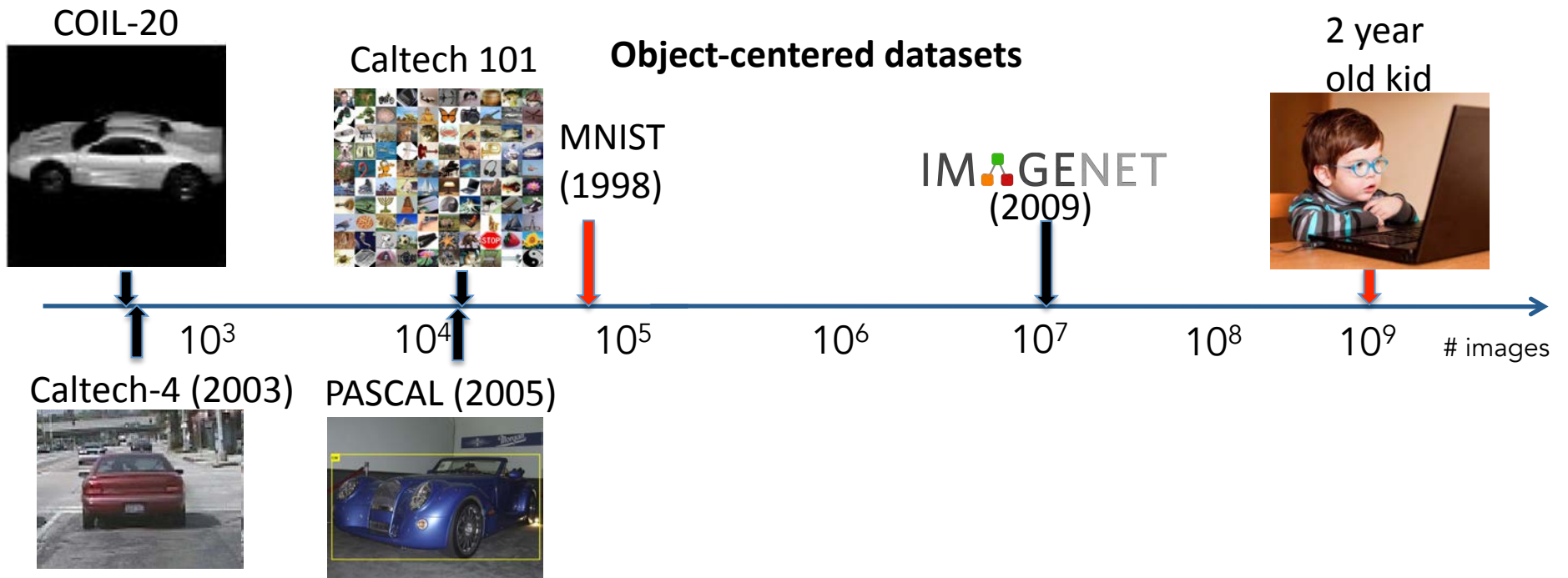
Output:  
Scale  
T-shirt  
Giant panda  
Drumstick  
Mud turtle

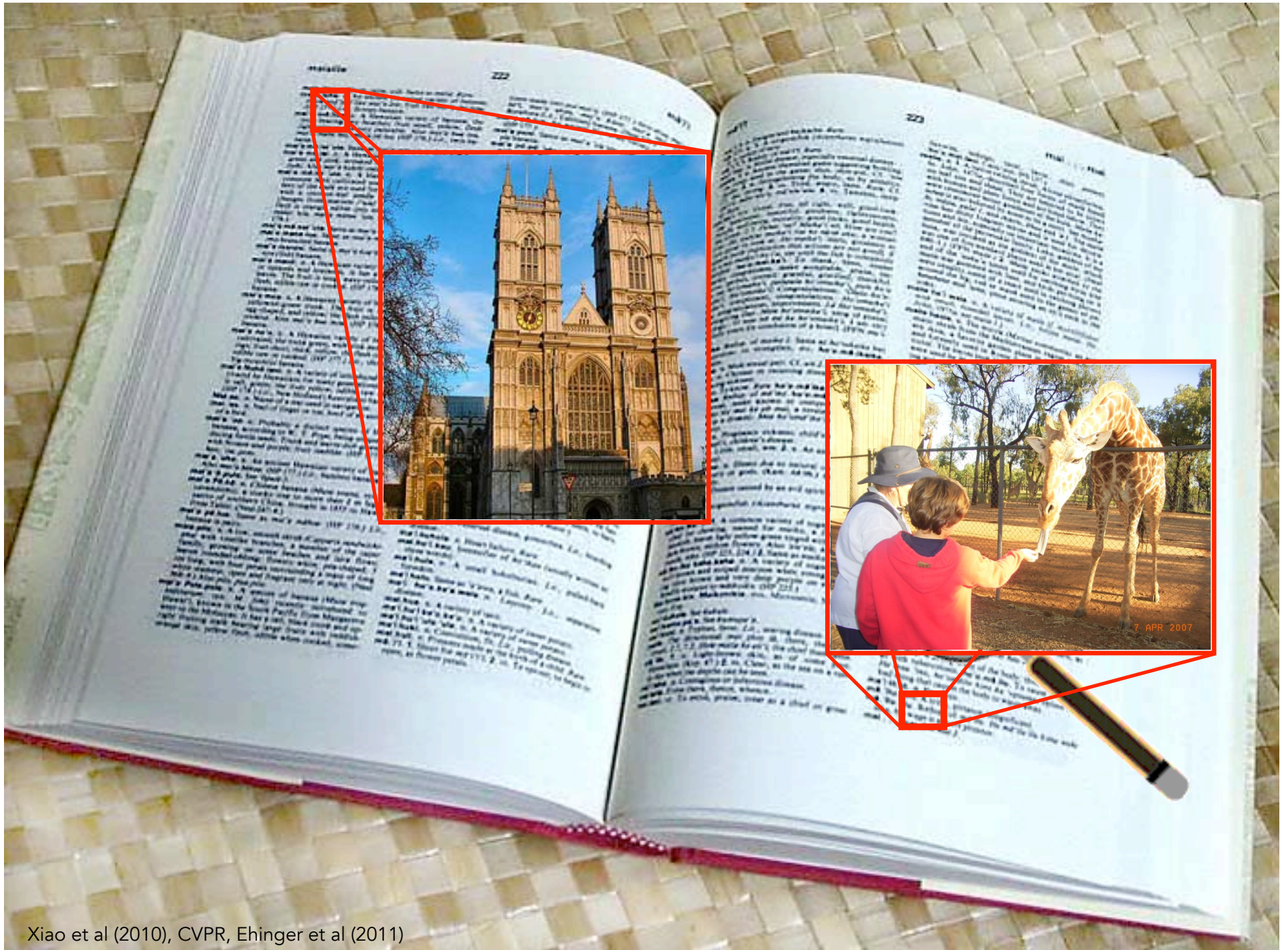


Russakovsky et al. arXiv, 2014



# The evolution of vision databases

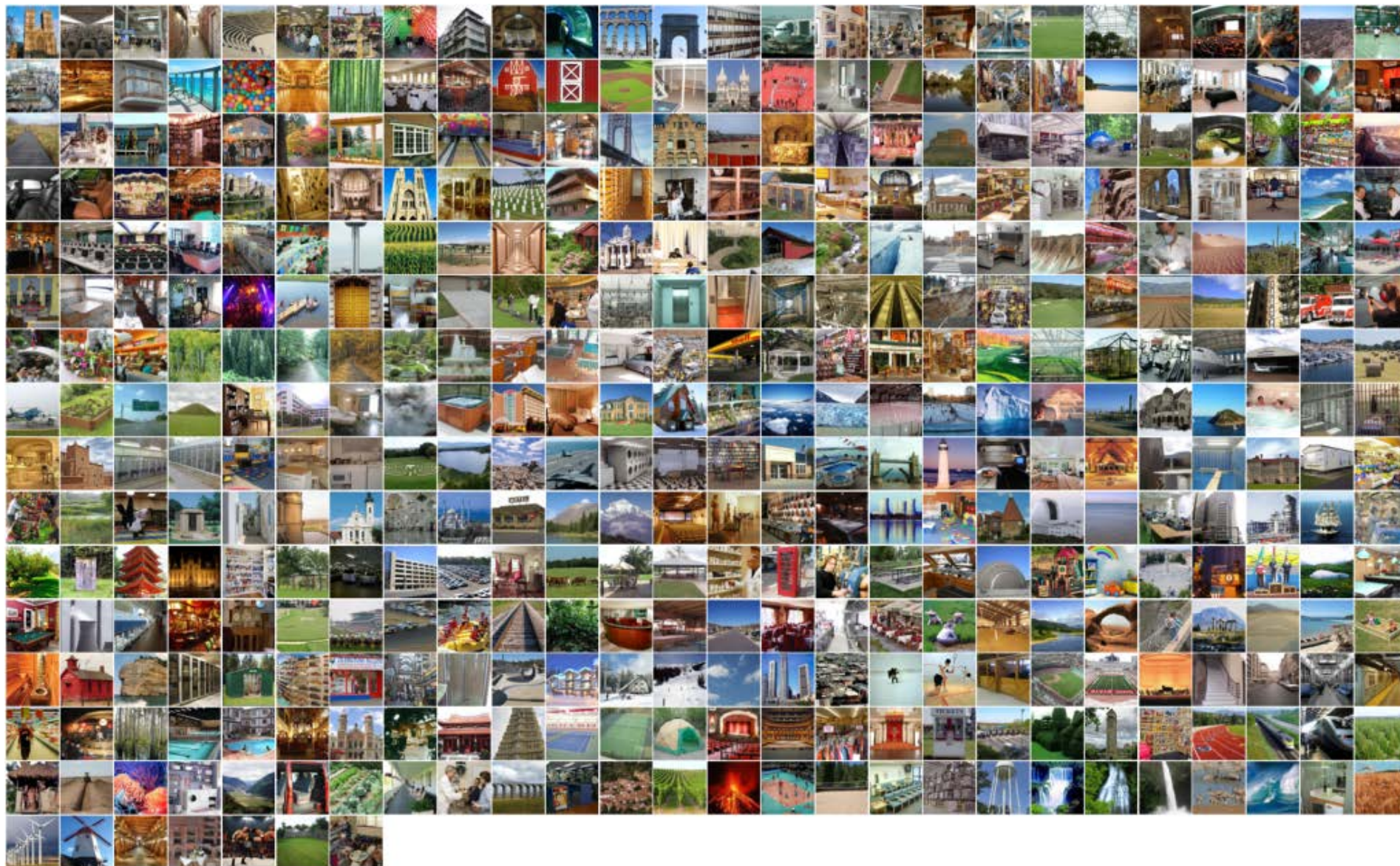




Xiao et al (2010), CVPR, Ehinger et al (2011)

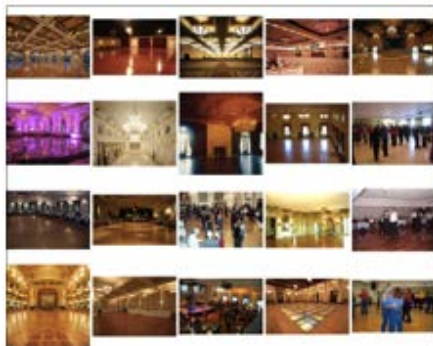


# SUN dataset: 900 Scene Categories & 130,000 images





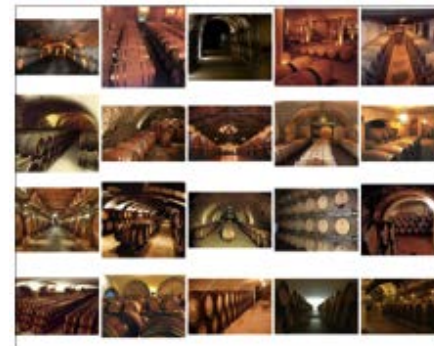
# SUN dataset: Entry-level category labels



Ballroom



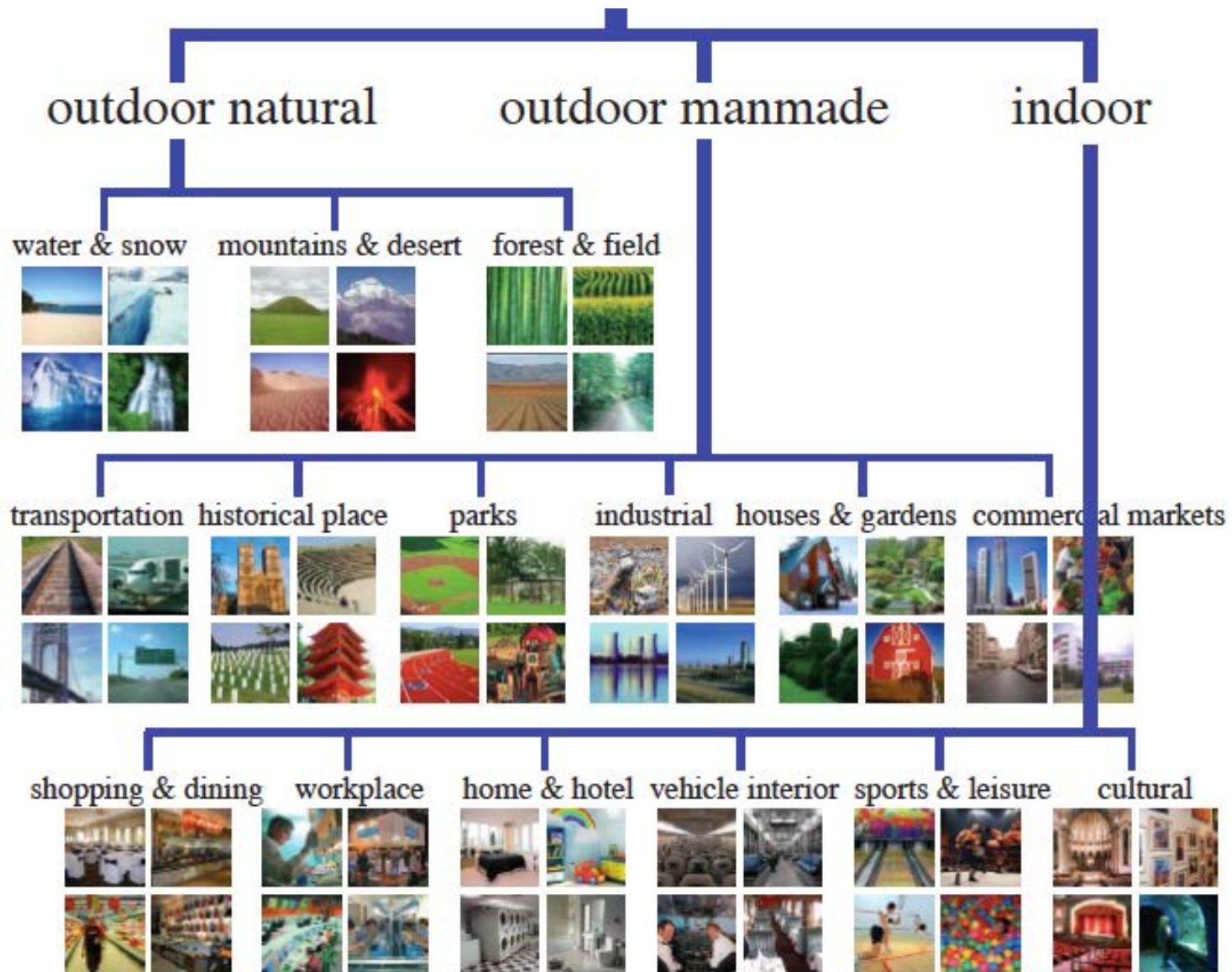
Car interior - backseat



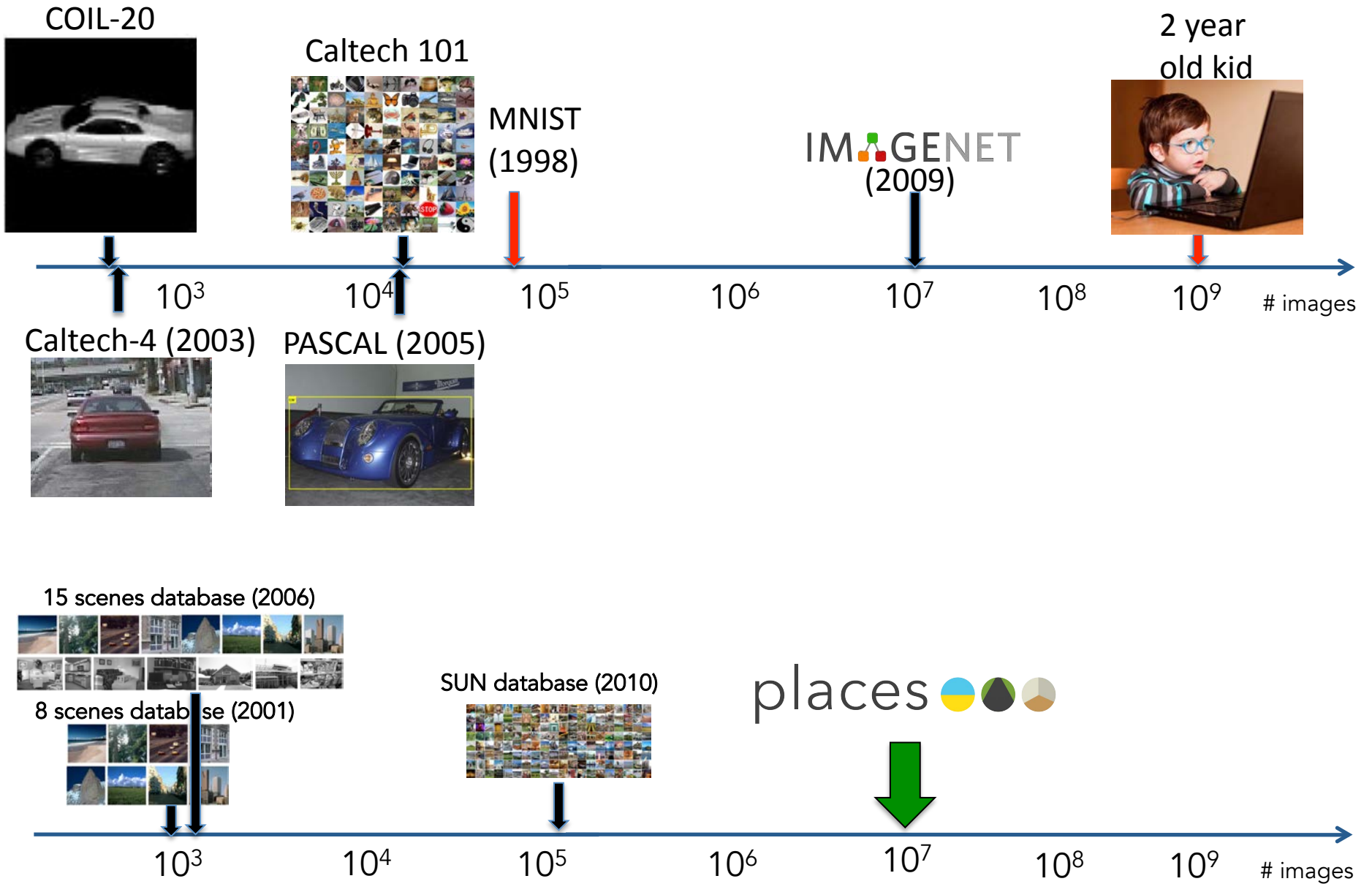
Wine cellar



# SUN dataset: Hierarchical organization



# The evolution of scene and object centered databases





Computation with millions of pictures of places, scenes, environments –  
*Where you and objects are*  
**Start with 60 million images**





Search

About 299,000,000 results (0.19 seconds)



SafeSearch off



Everything

Related searches: [bedroom designs](#) [master bedroom](#) [modern bedroom](#) [simple bedroom](#) [small bedroom](#)

Images

Maps

Videos

News

Shopping

More



Any time

Past 24 hours

Past week

Custom range...



All results

By subject

Personal

Any size

Large

Medium

Icon

Larger than...

Exactly...



Search

About 66,700,000 results (0.15 seconds)



SafeSearch off

Everything

Images

Maps

Videos

News

Shopping

More

Any time

Past 24 hours

Past week

Custom range...

All results

By subject

Personal

Any size

Large

Medium

Icon

Larger than...

Exactly...

Any color

Full color







www.bigstock.com - 7067629

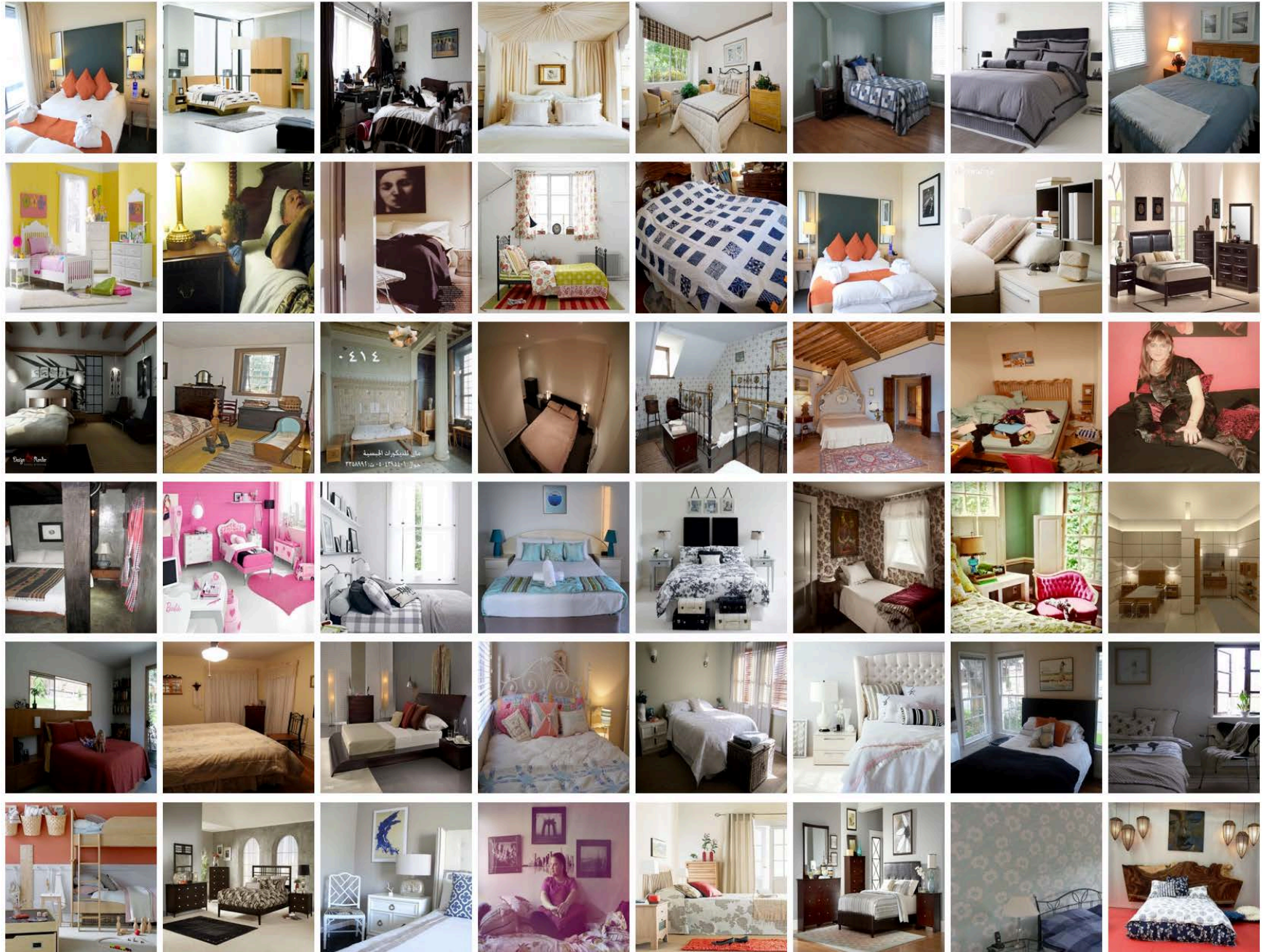


# Improving diversity

abandoned, acceptable, accessible, additional, adjacent, advertised, affordable, air-conditioned, alternative, american, amusing, ancient, antique, appealing, appropriate, architectural, asian, astonishing, astounding, attractive, austere, authentic, available, average, awesome, beautiful, beguiling, beloved, best, better, better-known, big, bigger, biggest, bizarre, black, black-and-white, bland, boring, breezy, brick-built, bright, brighter, brightest, brilliant, broken, busiest, business-like, bustling, busy, central, centralized, certain, changed, changing, charming, cheap, cheaper, cheapest, cheerful, cheerless, cheery, cherished, chilling, chilly, civilized, classic, classical, clean, cleaner, clear, clearer, clinical, closer, closest, closing, cloudy, coastal, cold, coldest, colourful, comfortable, comforting, comfortless, comfy, common, comparable, comparative, competitive, complementary, complete, complex, complicated, concealed, conceivable, confined, considerable, contemporary, cool, coolest, cosmopolitan, cost-effective, cosy, cozy, cream-white, creative, crowded, cultivated, cultural, current, damp, dangerous, dark, darkened, darker, darkest, decorative, delightful, designated, designed, desirable, desired, desolate, desolated, different, difficult, dilapidated, dim, dimly-lit, dingy, dirty, disadvantageous, disorderly, do-it-yourself, domestic, double, double-fronted, double-length, downtown, drab, dreadful, driest, dry, dual, dull, duller, dullest, dusty, early, economic, economical, elegant, embarrassing, empty, enormous, especial, european, everyday, exciting, exemplary, exotic, exterior, external, extraordinary, extravagant, familiar, famous, fancy, fantastic, far-away, fascinating, fashionable, fashioned, favourable, fictional, fictitious, filmed, filthy, fine, foggy, foreign, formal, fractured, friendly, frightening, frightful, frosty, frozen, frustrating, full, funny, furnished, fuzzy, gaudy, ghastly, ghostly, glamorous, glassy, glazed, glittering, gloomy, glorious, glossy, godlike, gold-plated, good, gorgeous, graceful, gracious, grand, gray, great, greatest, green, greener, grey, grisly, gruesome, habitable, habitual, handy, happy, harmonious, harrowing, harsh, hazardous, healthful, healthy, heart-breaking, heart-rending, heavy, hideous, hiding, higgledy-piggledy, high, hilarious, historic, historical, holiest, home, horizontal, hospitable, hostile, hot, huge, humid, idyllic, illegal, imaginary, immaculate, immense, imminent, immortal, impassable, impassioned, impersonal, important, impossible, impressive, improbable, improper, inauspicious, inconceivable, inconvenient, incredible, independent, individual, indoor, industrial, ineffable, inexpensive, informal, inhabited, inhospitable, initial, innovatory, innumerable, insecure, insignificant, inspiring, integrated, intentional, interesting, intermediate, internal, international, intimidating, intriguing, inviting, irrational, irregular, isolated, joint, joyful, key, known, large, large-scale, largest, less-favored, lesser, licensed, lifeless, light, limited, little, little-frequented, little-known, lively, living, local, lofty, logical, lone, long, long-awaited, long-forgotten, long-inhabited, long-netting, long-stays, long-term, lost, lousy, lovely, low, low-ceilinged, low-cost, low-energy, lower, lucky, luxury, magical, magnificent, main, majestic, major, marginal, marine, marvellous, massive, masterful, maximum, mean, meaningless, mechanised, medieval, mediocre, medium-sized, melancholy, memorable, messy, middle, middle-order, mighty, miniature, minor, miserable, missing, misty, mixed, modern, moist, mouldy, mountainous, moving, muddy, multi-functional, multiple, mundane, murky, musty, muted, mysterious, mysterious-looking, mystic, mystical, mythic, naff, named, nameless, narrow, national, native, natural, naturalistic, nearby, neat, necessary, neglected, neighboring, new, nice, night-time, nineteenth-century, noisy, nondescript, normal, northern, notable, notorious, numerous, odd, odorous, official, old, only, open, open-air, operatic, orderly, ordinary, organic, original, ornamental, out-of-homes, out-of-the-way, outdoor, outlying, outside, outstanding, over-crowded, overgrown, overwhelming, paid, painful, painted, palatial, pastoral, peaceful, peculiar, perfect, periodic, peripheral, permanent, permitted, personal, petty, pictorial, picturesque, pitiful, placid, plain, planted, pleasant, pleasing, poisonous, poor, popular, populated, populous, positive, possible, post-war, posterior, postmodern, potential, powerful, practical, pre-arranged, pre-eminent, precise, predictable, present, present-day, preserved, pretty, previous, pricey, primal, prior, private, privileged, probable, professional, profitable, promising, proven, public, pure, queer, quiet, rainy, rare, real, realistic, reasonable, rebuilt, recent, recognized, recommended, reconstructed, recreated, recurring, red, red-brick, redundant, refused, regional, regular, related, relative, relaxing, relevant, reliable, religious, remaining, remarkable, remote, rented, representative, reputable, required, reserved, residential, respectable, respected, restful, restless, restricted, retail, rich, ridiculous, right, rigid, river-crossing, rocky, romantic, rural, sacred, sad, safe, salubrious, satisfying, scary, scattered, scenic, scientific, secondary, secret, secured, selected, senior, separated, serious, sexy, shiny, shocking, shoddy, short-term, significant, silent, silly, similar, simple, single, sizable, slack, small, smelly, smoke-free, smoking, snowy, sobering, soft, solid, sombre, soothing, sophisticated, sorrowful, sound-filled, southern, spare, spatial, special, specialized, spectacular, sporting, stable, standard, static, steady, stifling, strange, stressful, striking, stunning, stupendous, stupid, stylish, successful, sufficient, sunny, super, superb, superior, surrealistic, suspicious, symbolic, teenage, terrible, terrific, theoretical, thrilling, thriving, tidier, tight, tiny, tough, tragic, unattractive, unbelievable, uncertain, unchanging, uncharted, uncivilized, uncomfortable, unconventional, underground, underwater, undisturbed, uneven, unexpected, unfamiliar, unforgettable, unfriendly, unhappy, unhealthy, unimportant, unknown, unnatural, unnecessary, unparalleled, unpleasant, unsafe, unseemly, unsuitable, unusual, upmarket, urban, vague, valuable, varied, various, vertical, very, vibrant, virtual, visual, vital, vivid, voluntary, vulgar, vulnerable, wacky, waiting, warm, wealthy, weeping, weird, weird-looking, well-assured, well-defended, well-designed, well-hidden, well-insulated, well-known, well-lit, well-loved, well-ordered, well-organized, well-secured, well-sheltered, well-used, wet, white, whole, wicked, wide, widespread, wild, windy, wintering, wonderful, wondrous, wooded, wordless, working, worldly, worldwide, worst, worthwhile, worthy, wretched, wrong, young, yucky,

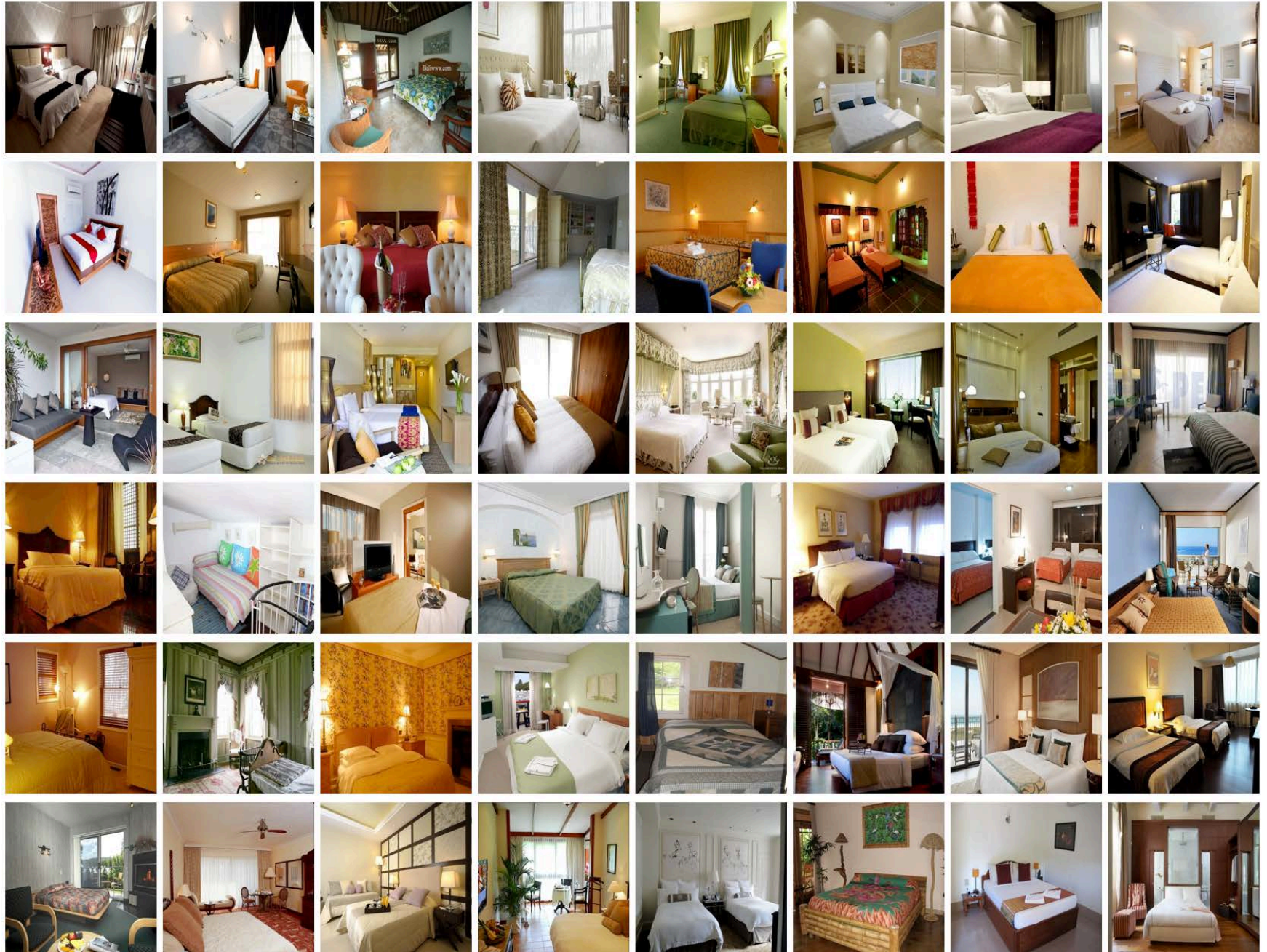


# simple bedroom:476



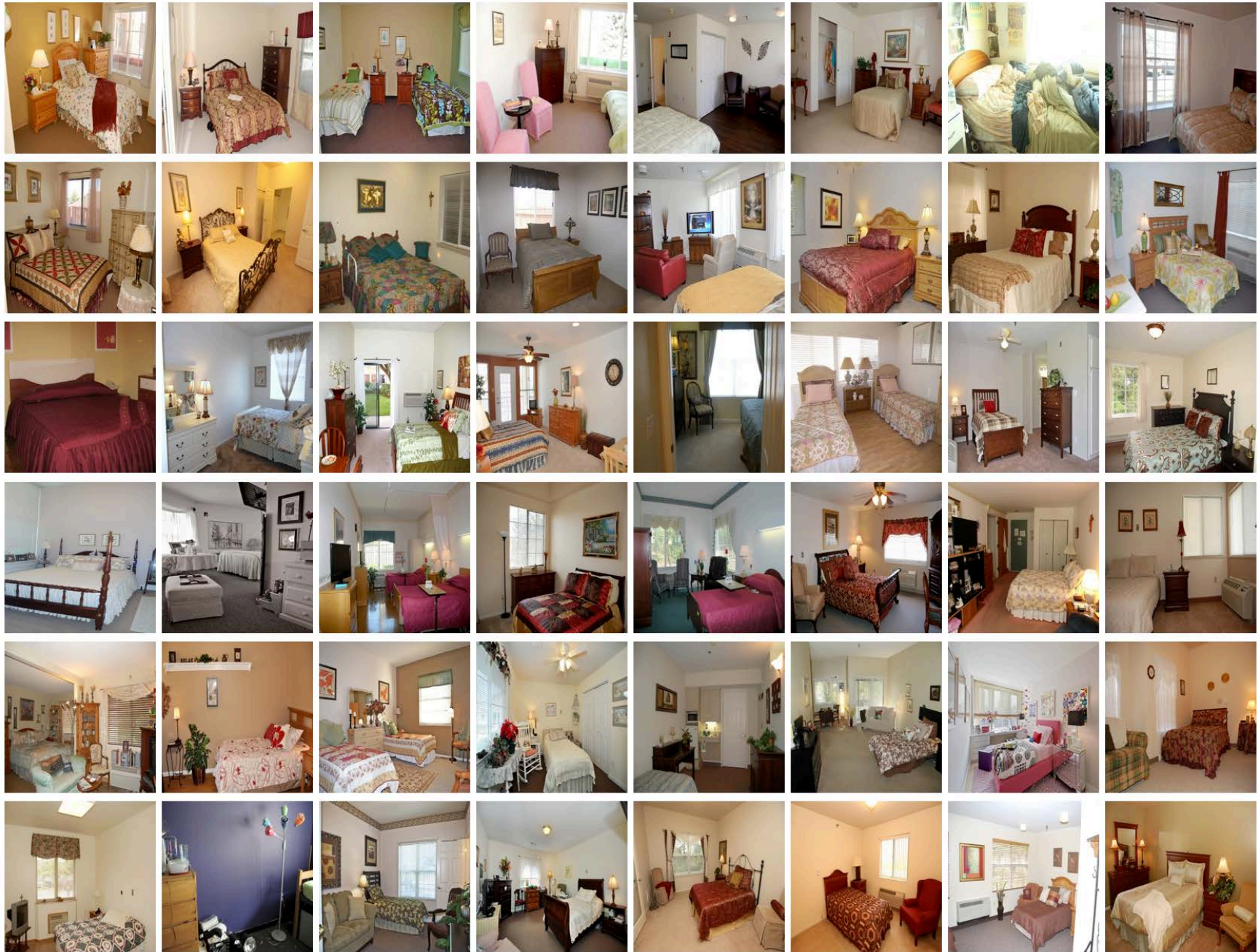


# superior bedroom:423



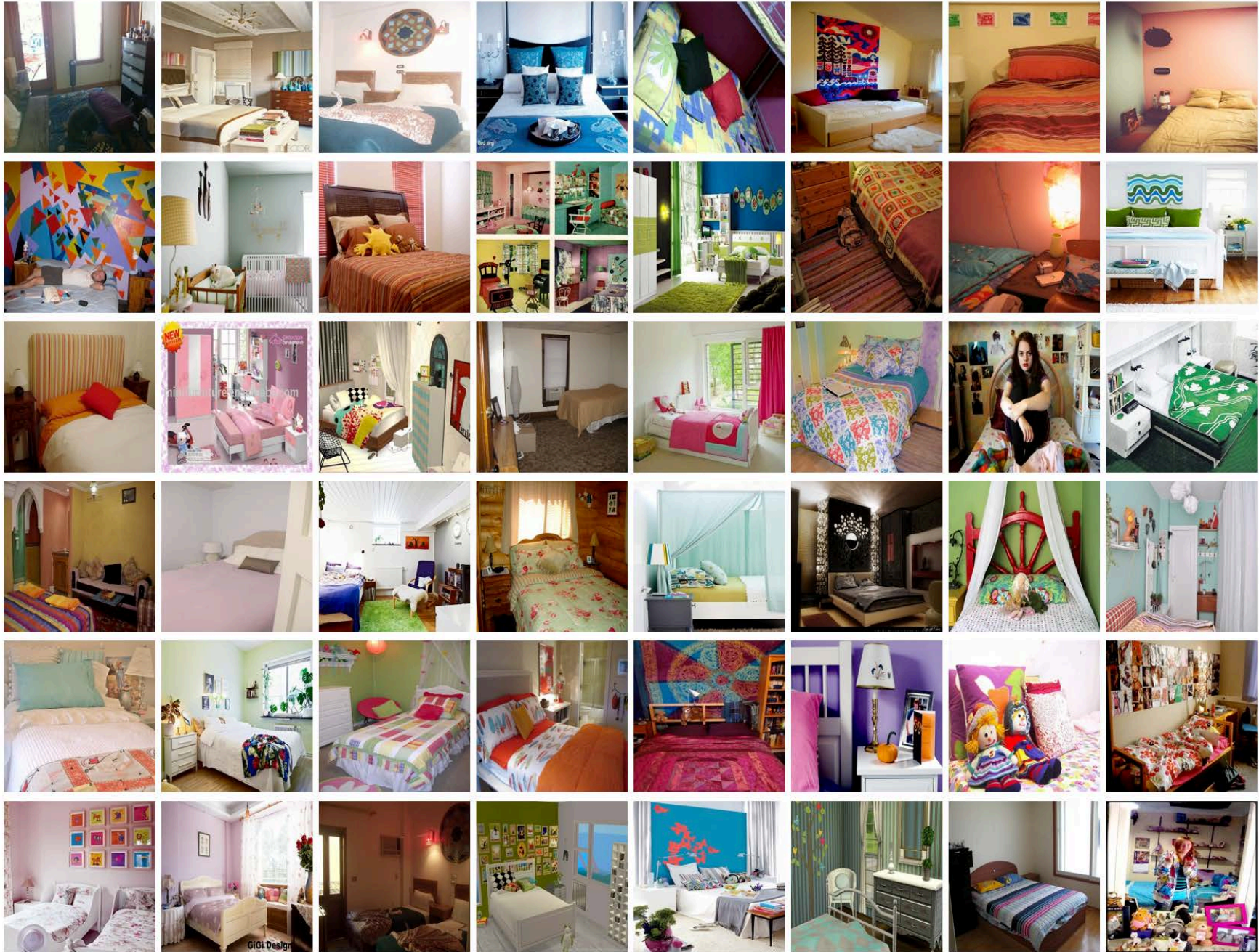


# senior bedroom:319



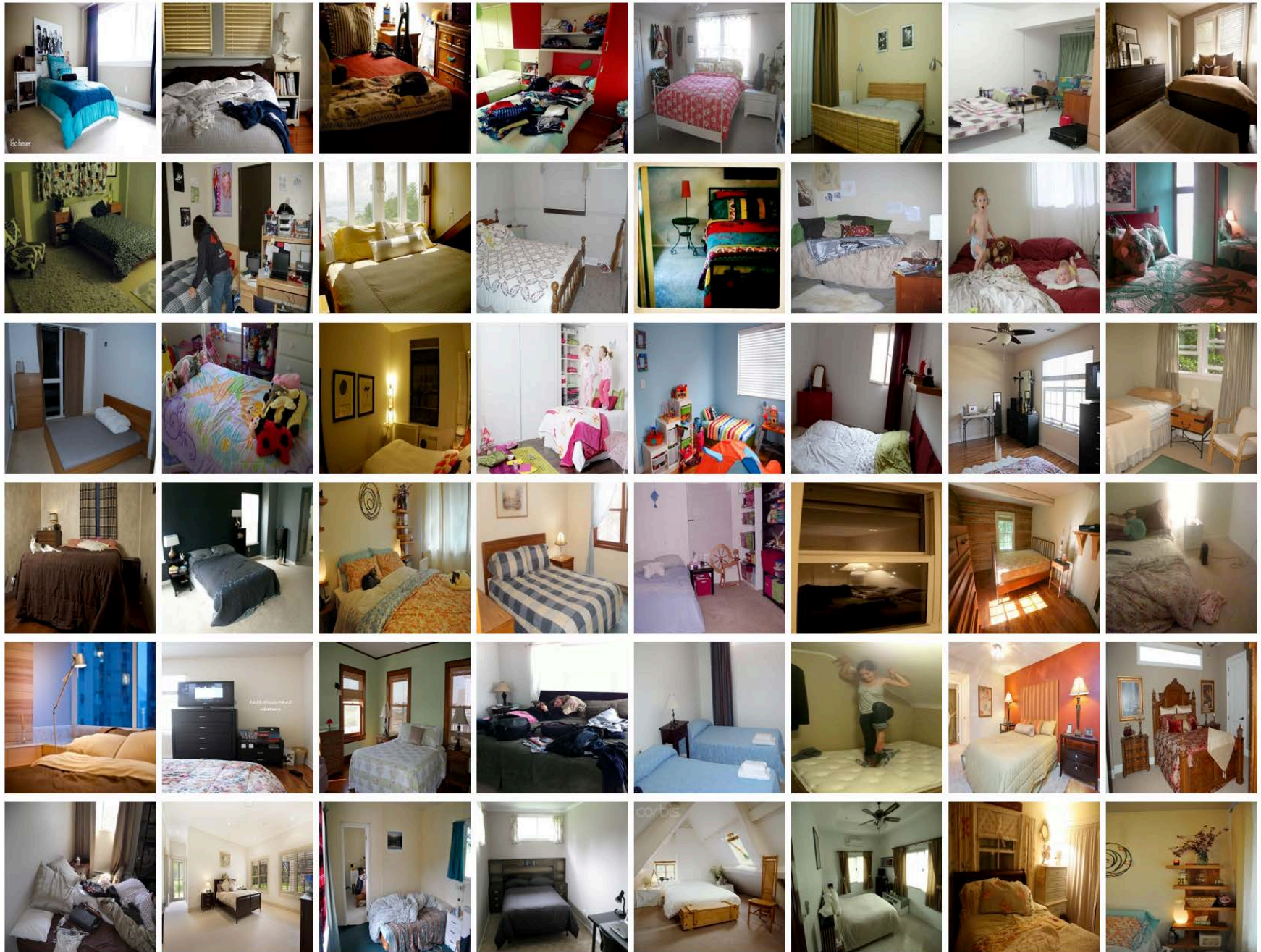


# colourful bedroom:209



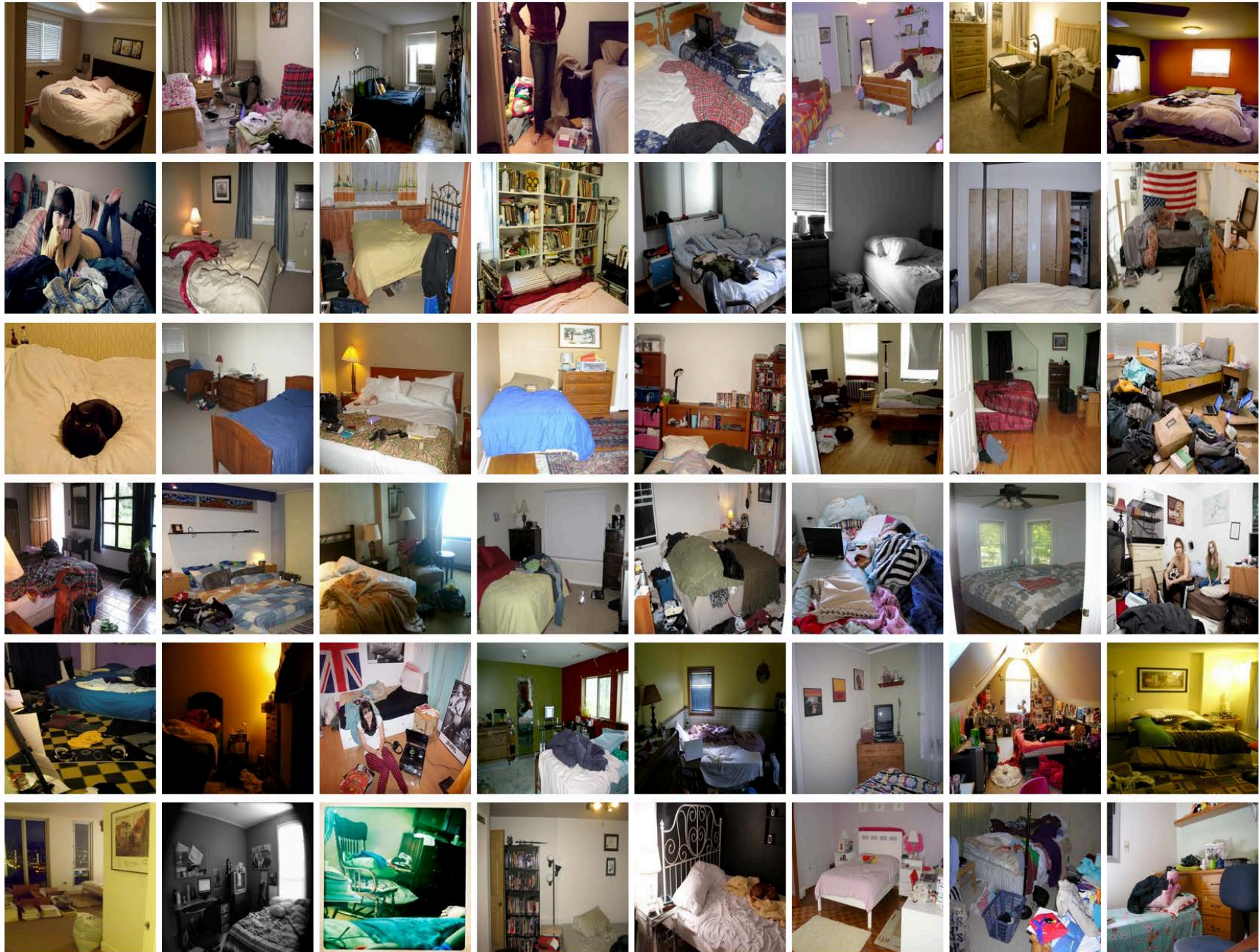


# cleaner bedroom:205





# messy bedroom:808





Start

# Is this a cliff scene?

**Definition:** a high, steep or overhanging face of rock.

## Task

For each of the **810** images, answer yes or no to the above question. Only answer **Yes** to **real photos**. Always answer **No** to **cartoon, drawing, CG rendering**, or real photos with a **large text overlay** on the photo. Here are some examples:

No Single Object No Text Overlay No Drawing No Screenshot No Graphics No Bad Photo



Not Only Logo No Magazine/Newspaper



Yes

Yes

Yes

Yes

Yes

Yes

Yes

Yes

Yes



# Amazon Mechanical Turk: Single Image Classification

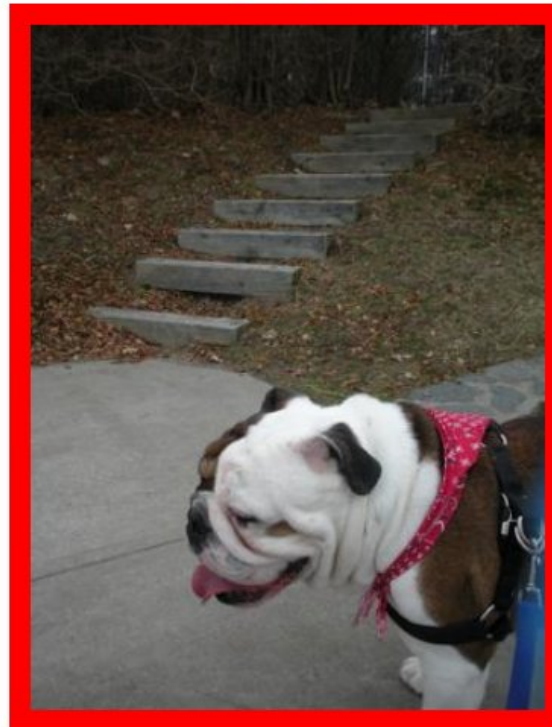
Instruction

**Is this a cliff scene?**

Submit (790 images left)

**Definition:** a high, steep or overhanging face of rock.

No





# Amazon Mechanical Turk: Single Image Classification

Instruction

**Is this a cliff scene?**

Submit (790 images left)

**Definition:** a high, steep or overhanging face of rock.

Yes



No



No



No



No



# Amazon Mechanical Turk: Single Image Classification – Second

Instruction

**Is this a living room scene?**

Submit (798 images left)

**Definition:** a room in a private residence intended for general social and leisure activities.

Yes



Yes



Yes



Yes





bookstore



dining room



gorge



mosque



glacier



toyshop



ocean deep



rock arch



reception

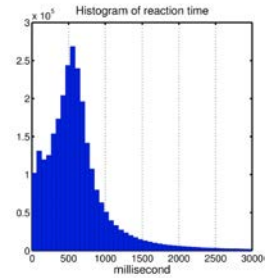




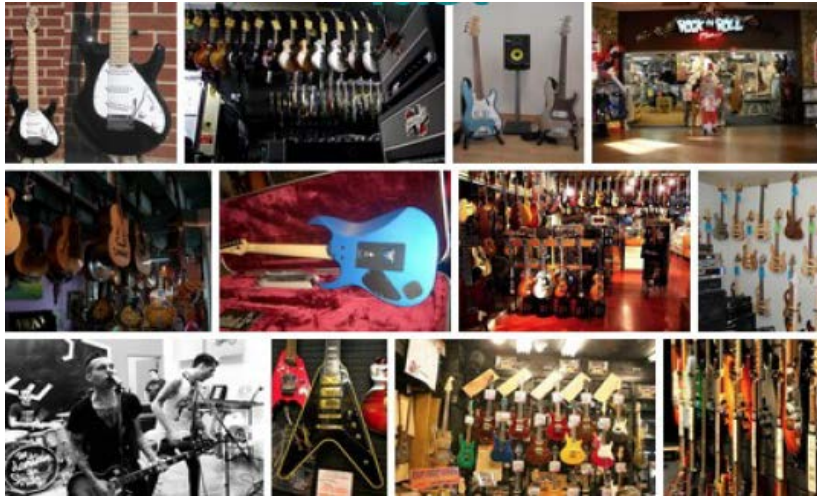
# A signature of Prototypicality

Fast RT

Slow RT



Music Store



Phone Booth





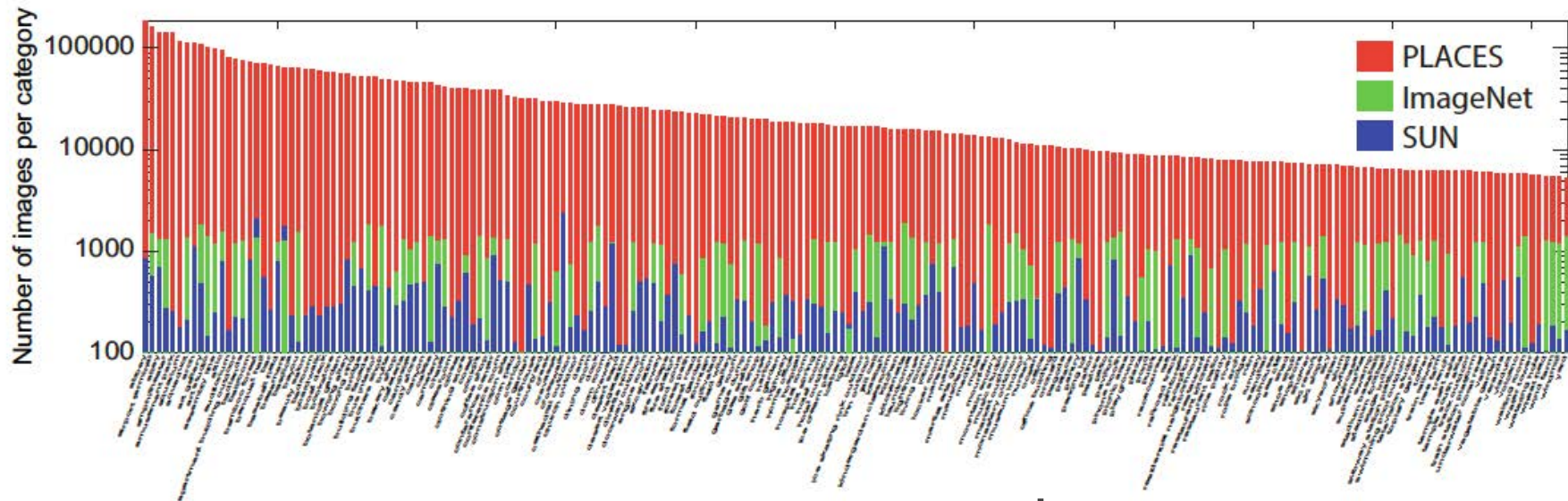
# High coverage across categories



# High diversity within category

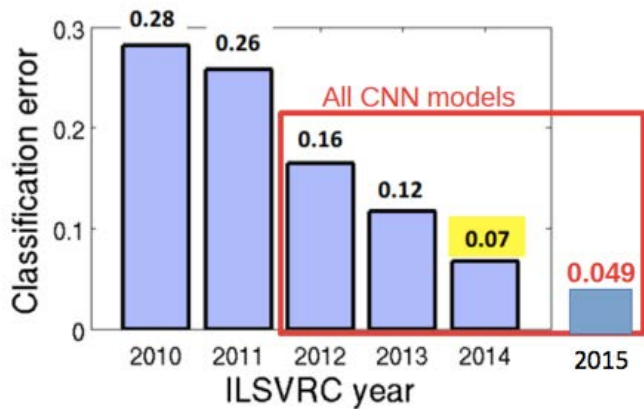


# places



IMAGENET 

places 

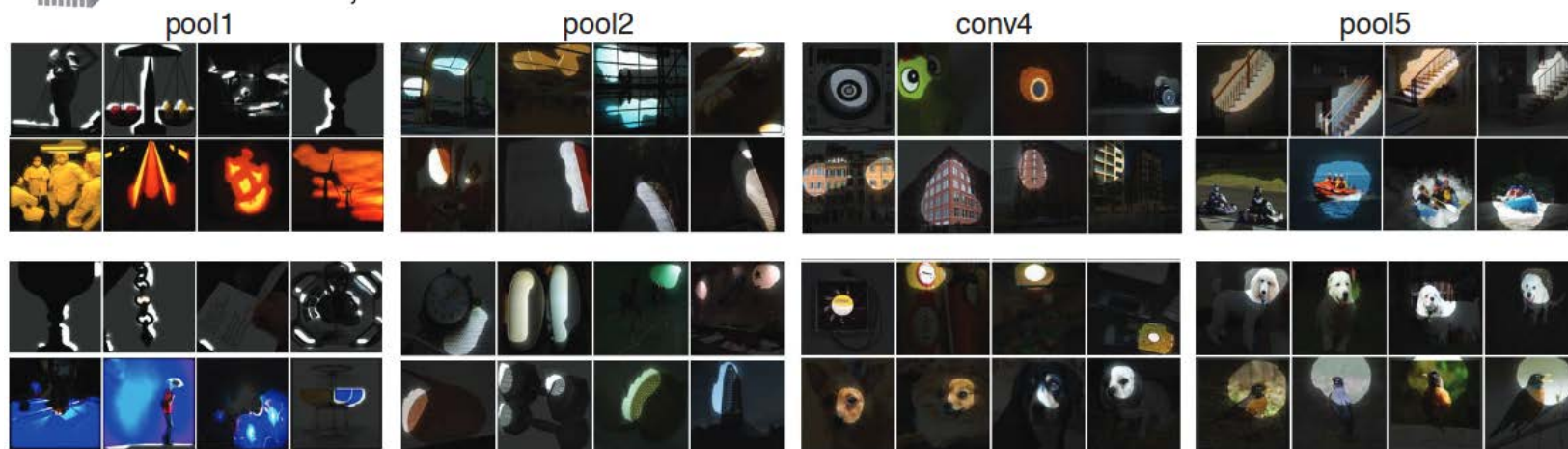
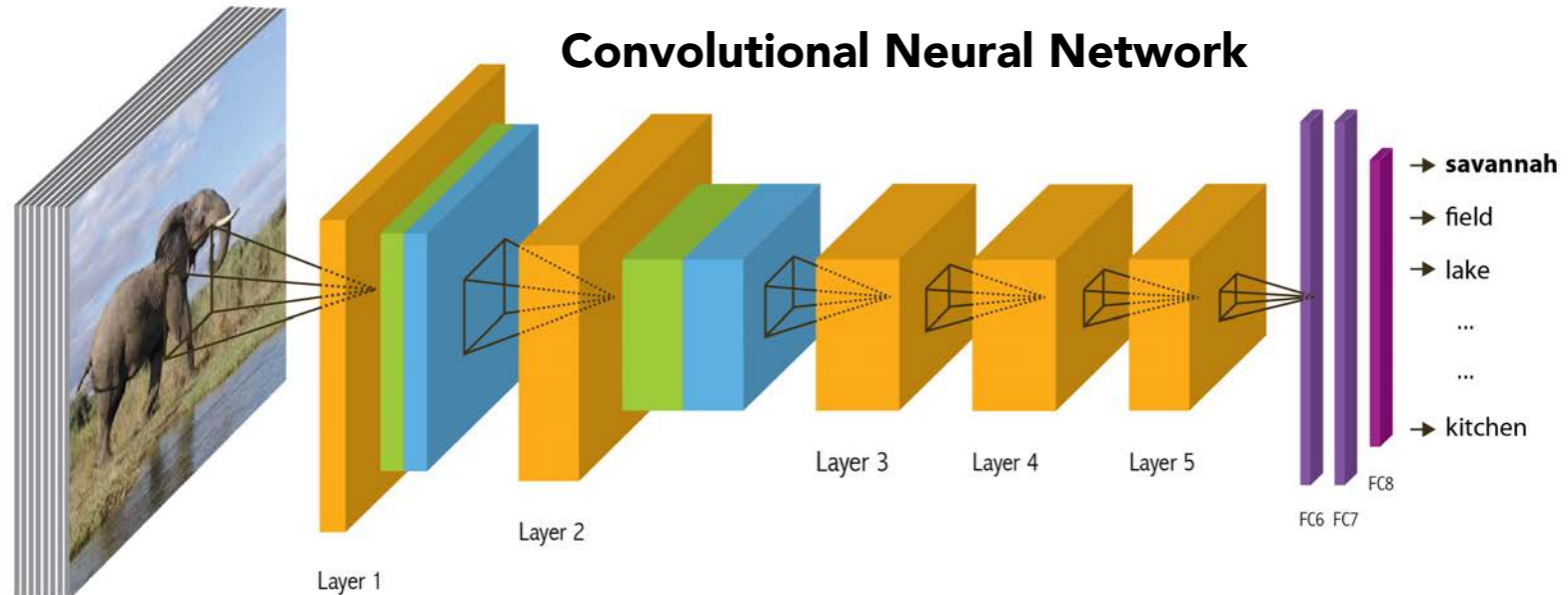


Nov 2015: Top 5 error: 25%



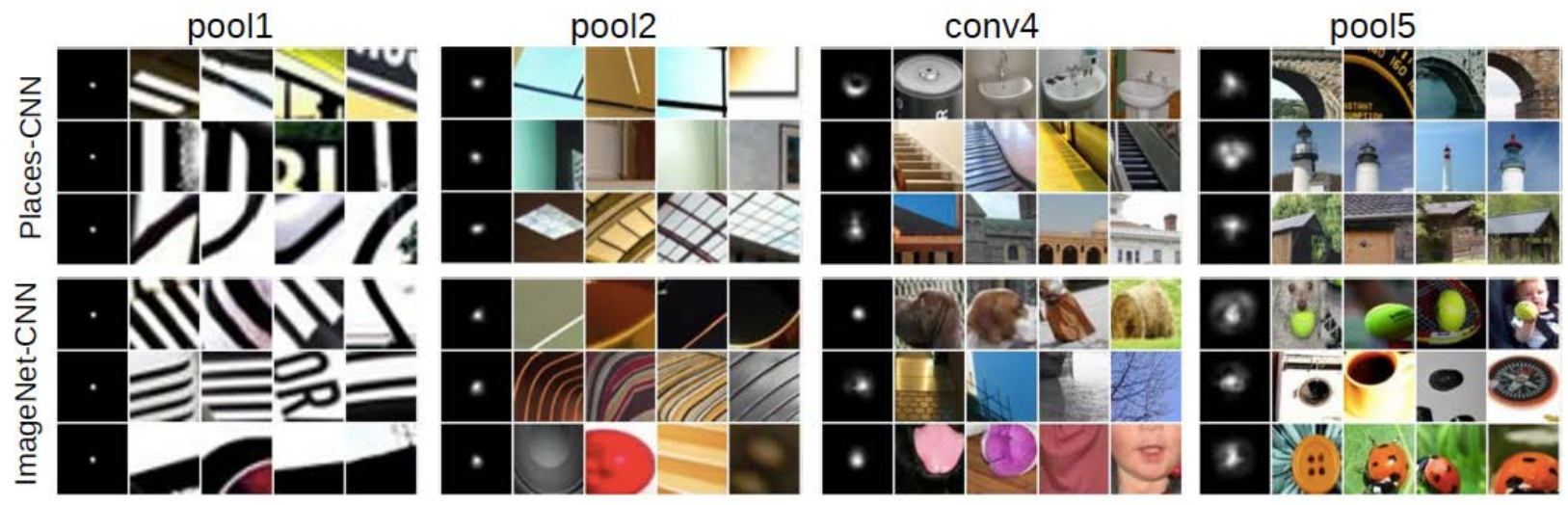
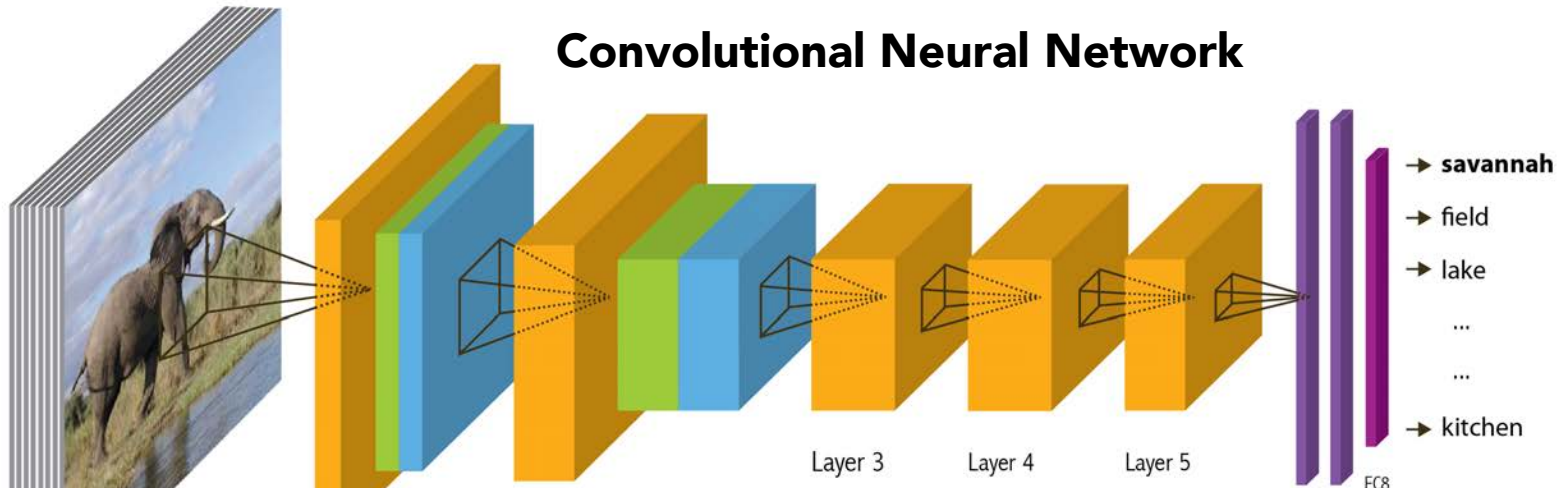
# places

 Convolution  Max pooling  Normalization  Fully connected



# places

Convolution
  Max pooling
  Normalization
  Fully connected



→  
 More semantically meaningful



# Mini Place challenge: 100 categories

## readme.txt

- Training data (100K - 1000 images per category),  
Validation data (10K, 100 images per category),  
Test data (10K – 100 images per category). Jpeg,  
128 \* 128
- Object annotations for a subset of the images –  
3503 train images and 371 validation images
- The evaluation server available from Tuesday Nov  
24 – submit your prediction of the test set for  
final evaluation and ranking in the challenge  
leaderboard. Open until Dec 1.
- Errors with 5 guesses will be used to rank the  
results and determine the winner

# Mini Place challenge

## Examples of things to do

- Train different types of classifiers such as classifiers on objects and scenes to improve scene classification
- Train a variety of networks and try ensemble methods (combine outputs from various networks trained with different random seeds and/or also networks with different architectures)
- Try averaging the prediction from multiple crops
- Try different architectures of deep networks on mini places dataset (different numbers of units per layer, types of activation functions for neurons for different layers, provide supervision to intermediate layers)
- Try out different learning parameters (i.e., learning rate, weight decay, momentum and so on) to maximize performance