# **Image Classification**

- Introduction to Image Classification
- Challenges
- A simple Image Classification Pipeline
- Data Sets

#### Image Classification: A core computer vision task

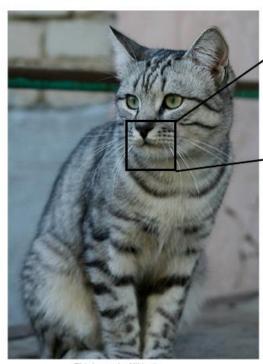
#### Input: image



**Output**: Assign image to one of a fixed set of categories

cat
bird
deer
dog
truck

# Problem: Semantic Gap



This image by Nikita is licensed under CC-BY 2.0

[[105	112	108	111	104	99	106	99	96	103	112	119	104	97	93	87]
[ 91	98	102	106	104	79	98	103	99	105	123	136	110	105	94	85]
[ 76	85	90	105	128	105	87	96	95	99	115	112	106	103	99	85]
[ 99	81	81	93	120	131	127	100	95	98	102	99	96	93	101	94]
[106	91	61	64	69	91	88	85	101	107	109	98	75	84	96	95]
[114	108	85	55	55	69	64	54	64	87	112	129	98	74	84	91]
[133	137	147	103	65	81	80	65	52	54	74	84	102	93	85	82]
[128	137	144	140	109	95	86	70	62	65	63	63	60	73	86	101]
[125	133	148	137	119	121	117	94	65	79	89	65	54	64	72	98]
[127	125	131	147	133	127	126	131	111	96	89	75	61	64	72	84]
[115	114	109	123	150	148	131	118	113	109	100	92	74	65	72	78]
[ 89	93	90	97	108	147	131	118	113	114	113	109	106	95	77	80]
[ 63	77	86	81	77	79	102	123	117	115	117	125	125	130	115	87]
[ 62	65	82	89	78	71	80	101	124	126	119	101	107	114	131	119]
[ 63	65	75	88	89	71	62	81	120	138	135	105	81	98	110	118]
[ 87	65	71	87	106	95	69	45	76	130	126	107	92	94	105	112]
[118	97	82	86	117	123	116	66	41	51	95	93	89	95	102	107]
[164	146	112	80	82	120	124	104	76	48	45	66	88	101	102	109]
[157	170	157	120	93	86	114	132	112	97	69	55	70	82	99	94]
[130	128	134	161	139	100	109	118	121	134	114	87	65	53	69	86]
[128	112	96	117	150	144	120	115	104	107	102	93	87	81	72	79]
[123	107	96	86	83	112	153	149	122	109	104	75	89	107	112	99]
[122		102	80	82	86	94	117	145	148	153	102	58	78	92	107]
 [122	164	148	103	71	56	78	83	93	103	119	139	102	61	69	84]]

What the computer sees

An image is just a big grid of numbers between [0, 255]:

e.g. 800 x 600 x 3 (3 channels RGB)

#### Image Classification: Very Useful!

# Medical Imaging Benign Benign Malignant Malignant Benign Levy et al, 2016 Figure reproduced with permission

Galaxy Classification

From left to a left to a left of domain to 1935 h. uson operations to 1935 h. u

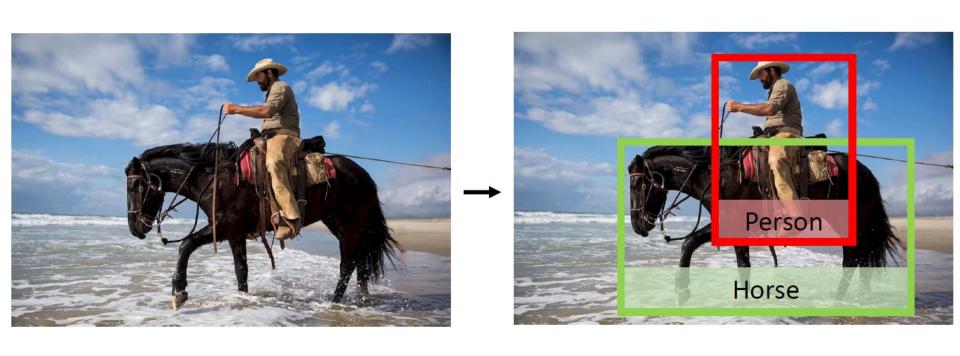
Dieleman et al, 2014

om left to right: public domain by NASA, usage permitted by ESA/Hubble, public domain by NASA, and public domain.

# Whale recognition Kaggle Challenge This image by Christin Khan is in the public domain and originally came from the U.S. NOAA.

#### Image Classification: Building Block for other tasks!

#### Object Detection



#### Image Classification: Building Block for other tasks!

#### Image Captioning



riding cat horse man when

<STOP>

What word to say next?

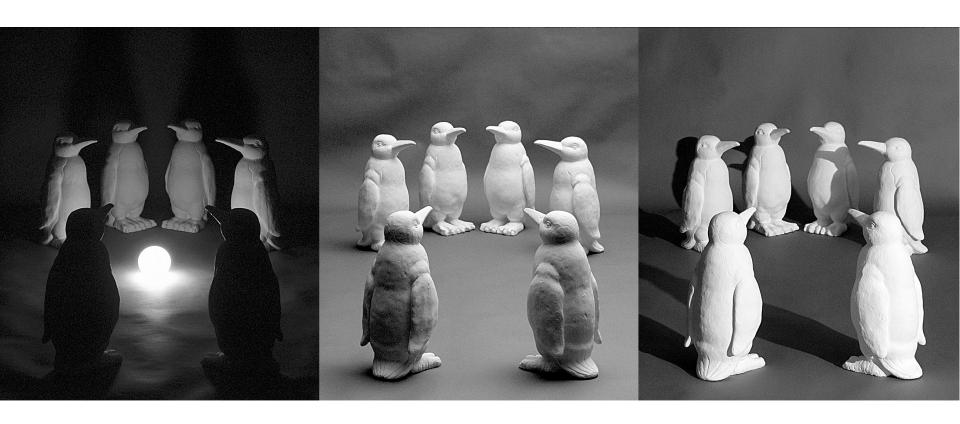
Caption: Man riding horse

#### Challenges: Viewpoint Variation









# Challenges: Scale



# Challenges: Deformation





# Challenges: Occlusion





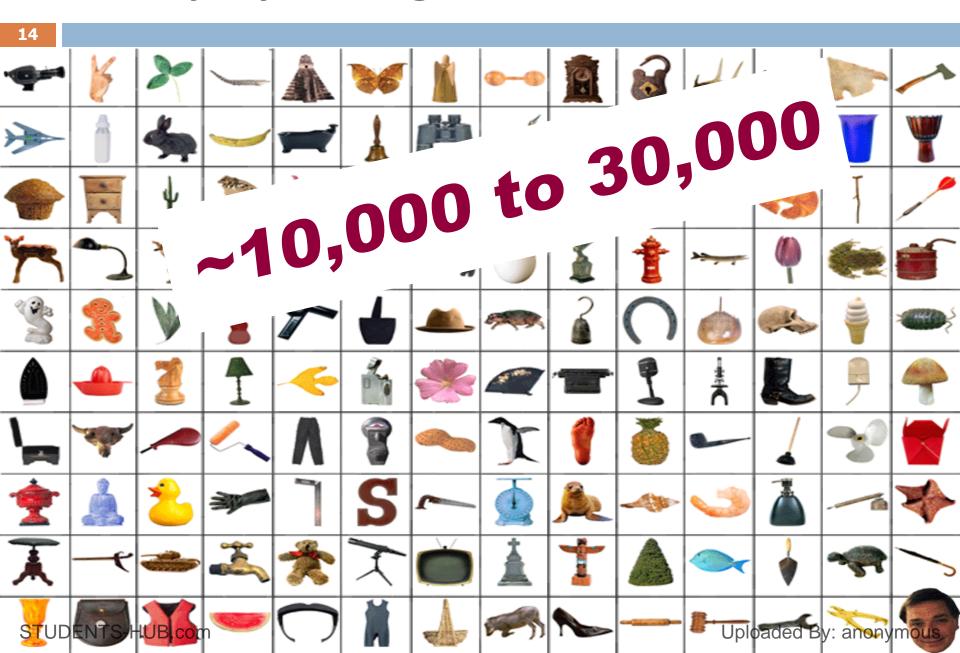


# Challenges: Background Clutter





# How many object categories are there?



## Categorization vs Single instance recognition

#### Where is the crunchy nut?





# **Challenges: Intra-class variation**









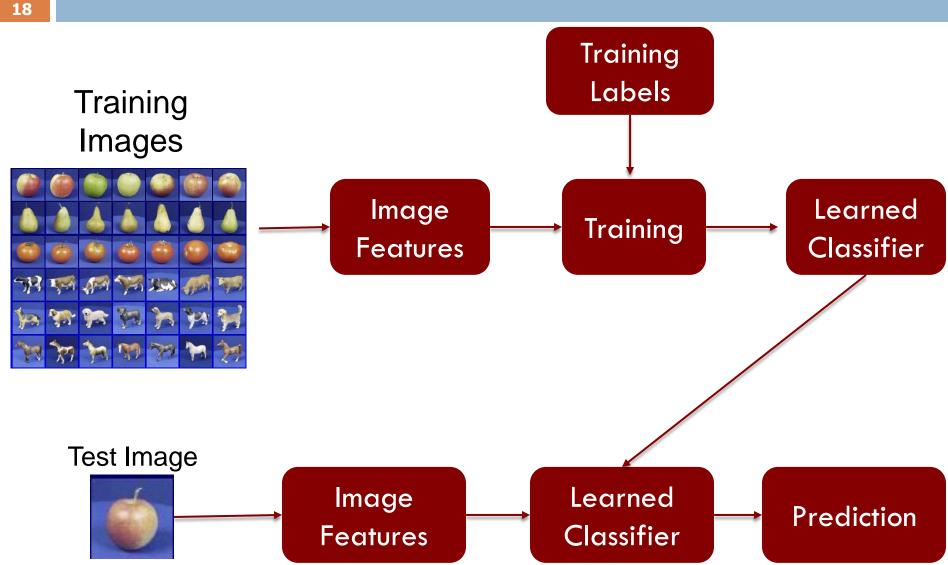




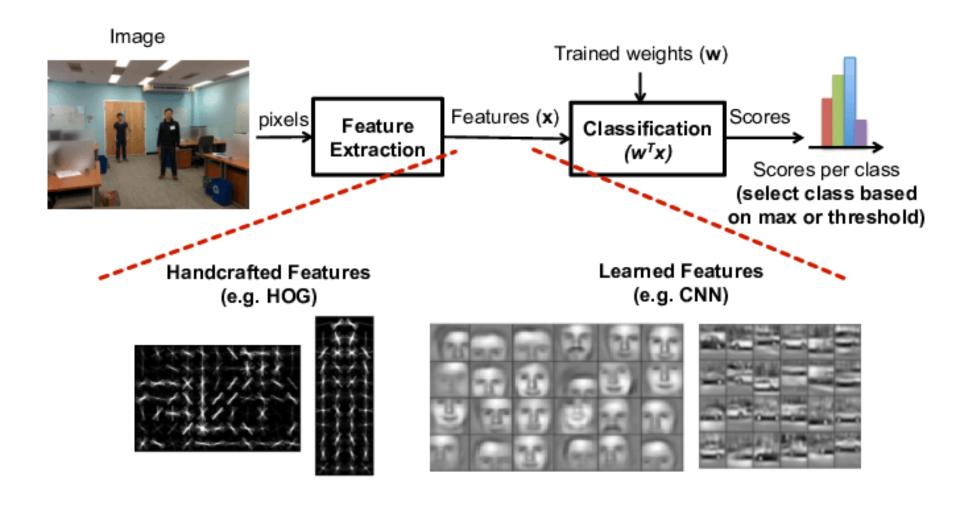
## **Image Classification Pipeline**

- □ The pipeline typically consists of the following steps:
  - 1. Data collection and preparation: This involves collecting a large and diverse dataset of images, labeled with their corresponding categories. The images should be preprocessed to ensure that they are in a consistent format and size.
  - 2. **Feature extraction**: This involves extracting features from the images that can be used to train the machine learning model. Features can be extracted using a variety of methods, such as hand-crafted algorithms or deep learning models.
  - 3. **Model training**: This involves training a machine learning model on the extracted features. The model learns to identify the patterns in the features that are associated with different categories.
  - 4. **Model evaluation**: This involves evaluating the performance of the trained model on a held-out test set. The evaluation results are used to assess the model's accuracy and generalization ability.
  - 5. **Model deployment**: Once the model is trained and evaluated, it can be deployed to production to classify new images.





#### **Feature Extraction Techniques**



# **Feature Extraction Techniques**

Aspect	Handcrafted Features	Learned Features (Deep Learning)
<b>Control Over Feature Selection</b>	Full control based on domain knowledge.	Features are automatically learned from data.
Interpretability	More interpretable, as features are explicit.	Often considered as "black boxes" with less interpretability.
Performance on Large Datasets	May struggle with large datasets due to overfitting.	Excels on large datasets, capturing intricate patterns.
Data Representation Learning	Limited ability to learn data representations.	Learns hierarchical representations of data.
Problem Complexity	Suitable for well-understood problems.	Suitable for complex problems with unknown patterns.
Transfer Learning	Limited application due to handcrafted nature.	Can leverage pre-trained models for transfer learning.

#### Many classifiers to choose from

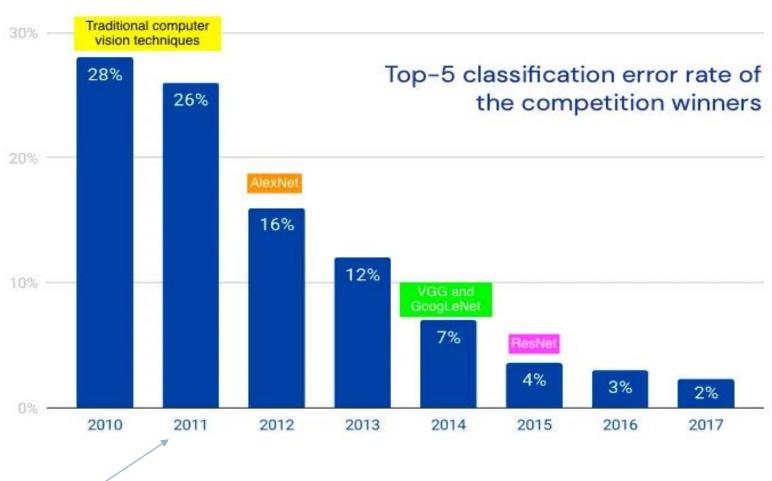
#### 21

- K-nearest Neighbor
- Decision Trees
- Naive Bayes
- SVM
- Random Forests
- XGBoost
- Neural Networks
- Convolutional neural network.
- □ .....

#### What is the best one?

CNNs have been shown to achieve state-of-the-art results on a variety of image classification tasks.

## **ImageNet Competition Winners**



Low-level feature extraction ≈ 10k patches per image

SIFT: 128-dim

• color: 96-dim STUDENTS-HUB.com

reduced to 64-dim with PCA

# Image Classification Datasets: MNIST



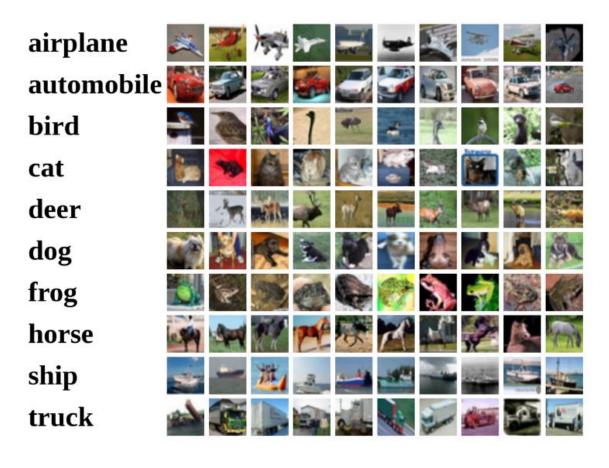
- **10 classes**: Digits 0 to 9
- 28x28 grayscale images
- 50k training images
- 10k test images

#### Image Classification Datasets: Fashion MNIST



- The dataset contains 60,000 training images and 10,000 testing images
- Consists of 28x28 grayscale images of fashion items,
- □ 10 categories.
- Each category represents a different type of clothing or accessory.

#### Image Classification Datasets: CIFAR10



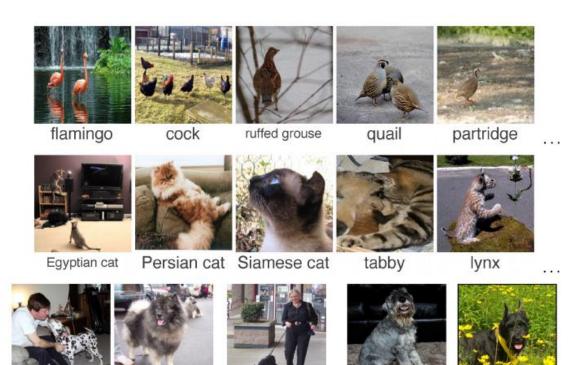
- 10 classes
- 50k training images(5k per class)
- 10k testing images(1k per class)
- □ **32x32 RGB** images

#### Image Classification Datasets: CIFAR100



- **100** classes
- 50k training images (500 per class)
- **10k** testing images (100 per class)
- 32x32 RGB images
- 20 superclasses with 5 classes each:
- Aquatic mammals: beaver, dolphin, otter, seal, whale
- Trees: Maple, oak, palm, pine, willow

#### Image Classification Datasets: ImageNet



miniature schnauzer standard schnauzer giant schnauzer

- **1000** classes
- ~1.3M training images (~1.3K per class)
- 50K validation images (50 per class)
- □ **100K** test images (100 per class)
- Performance metric: **Top 5**accuracy
- Algorithm predicts 5 labels for each image; one of them needs to be right
- There is also a 22k category version of ImageNet, but less commonly used

keeshond

dalmatian

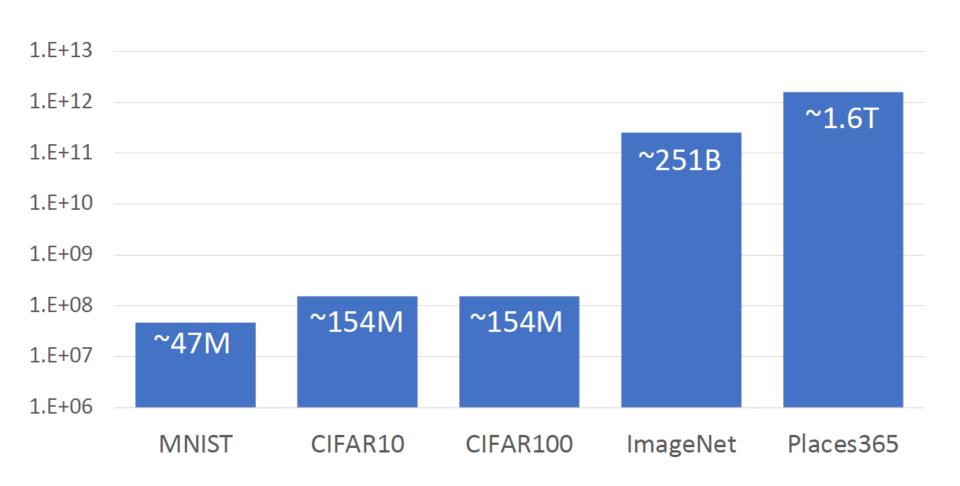
#### Image Classification Datasets: MIT Places





- 365 classes of different scene types
- □ ~8M training images
- 18.25K val images (50 per class)
- 328.5K test images (900 per class)
- Images have variable size, often
- resize to 256x256 for training

#### Classification Datasets: Number of Training Pixels



# Acknowledgement

- The material in these slides are based on:
  - Digital Image Processing: Rafael C. Gonzalez, and Richard
  - Forsythe and Ponce: Computer Vision: A Modern Approach
  - Rick Szeliski's book: Computer Vision: Algorithms and Applications
  - cs131@ Stanford University
  - cs131n@ Stanford University
  - CS198-126@ University of California, Berkely
  - CAP5415@ University of Central Florida
  - CSW182 @ University of California, Berkely
  - Deep Learning Lecture Series @UCL
  - EECS 498.008 @ University of Michigan
  - CSE576 @ Washington University
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