EECS 395/495 and Data_Sci 423
Machine Learning

Aggelos K. Katsaggelos

Joseph Cummings Professor
Northwestern University
Department of EECS
Department of Linguistics
Argonne National Laboratory
NorthShore University Health System
Evanston, IL 60208
http://ivpl.eecs.northwestern.edu

Outline

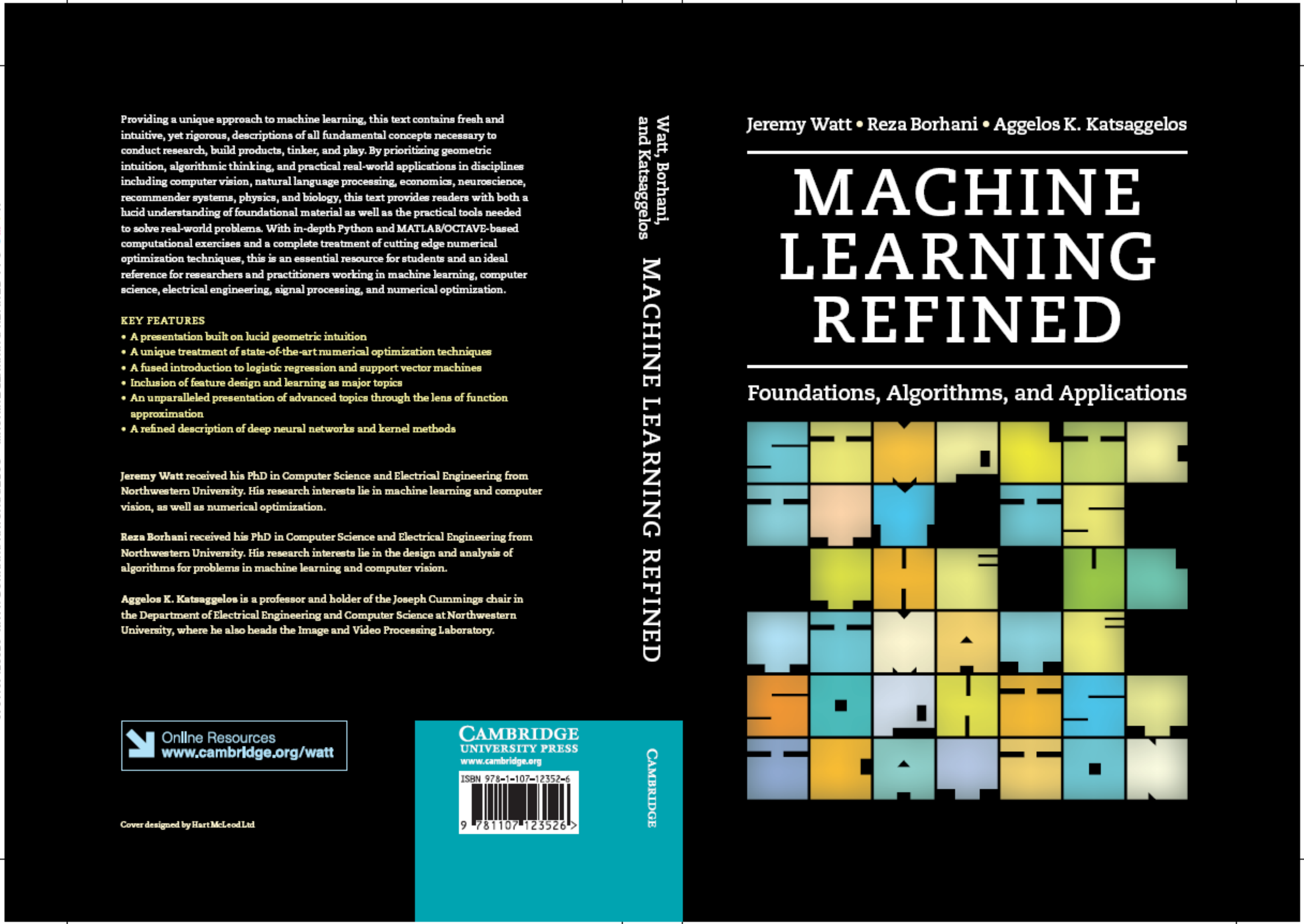
- Intro to Machine Learning and Numerical Optimization
- Regression
- Classification
- Function Approximation
- Bayesian Regression and Classification
- Matrix Factorization (K-Means, PCA, Recommender Systems,…)

Philosophy

- Depth vs Breadth
- Be able to derive and implement important ML algorithms
- Be able to easily expand your knowledge

Lecture 1

- What is Machine Learning
- Applications
- The two pillars: feature design and optimization
- Elements of Optimization



Download code + sample chapters
at www.mlrefined.com

What is Machine Learning

- A machine learning algorithm is an algorithm that is able to learn from data
- But what do we mean by learning?
- "A computer program is said to learn from ***experience E*** with respect to some class of ***tasks T*** and ***performance measure P***, if its performance at tasks in T, as measured by P, improves with experience E." (Mitchell 1997)

Task

- ML allows us to tackle tasks that are too difficult to solve with fixed programs written and designed by human beings
  - From a scientific and philosophical point of view, ML is interesting because developing our understanding of ML entails developing our understanding of the principles that underlie intelligence
- ML tasks are usually described in terms of how the machine learning system should process an example
  - An example is a collection of features that have been quantitatively measured from some object or event that we want the ML system to process

Common ML Tasks

- Classification $f: R^n \rightarrow \{1, \cdots, k\}$
- Classification with missing inputs (learn either all possible mappings or the joint distribution of all inputs which can be then marginalized over missing inputs)
- Regression $f: R^n \rightarrow R$
- Transcription (optical character recognition, speech processing)
- Structured outputs (any task where the output exhibits important *<u>relationships</u>* between the different elements, e.g., parsing a natural language segment, image segmentation, image captioning)

Common ML Tasks

- Anomaly detection (fraud detection; profile of user is build and used)
- Synthesis and Sampling (text to speech, video games: automatically generate textures for large objects)
- Imputation of missing values
- Denoising
- Density (or prob mass function) estimation

The Performance Measure

- Usually specific to the task T
- E.g. Classification
  - Accuracy (proportion of correct output)
  - Similarly: error rate (expected 0-1 loss)
- E.g. Density Estimation
  - Ave log probability the model assigns to some examples
- E.g. Transcription
  - Accuracy at transcribing entire sequences
  - Or more fine grained performance, e.g. partial credit for getting some words right
- E.g. Regression
  - should we penalize the system more if it frequently makes medium-sized mistakes or if it rarely makes very large mistakes?

The Experience E

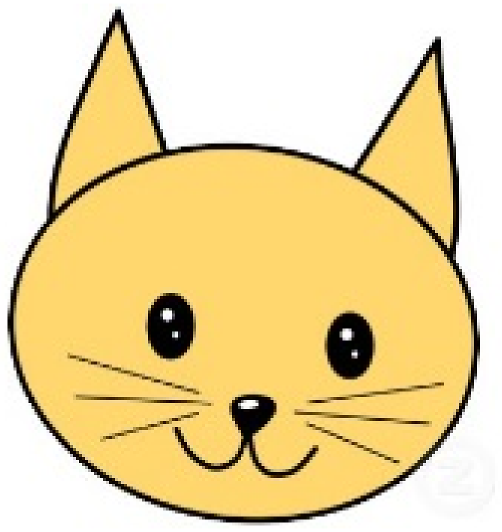
- Machine learning algorithms can be broadly categorized as ***unsupervised*** or ***supervised***
- Unsupervised learning algorithms experience a dataset containing many features, then learn useful properties of the structure of this dataset
- Supervised learning algorithms experience a dataset containing features, but each example is also associated with a label or target

The Experience E

- In ***semi-supervised learning*** some examples include a supervision target but others do not
- Some machine learning algorithms do not just experience a fixed dataset
  - For example, ***reinforcement learning algorithms*** interact with an environment, so there is a feedback loop between the learning system and its experiences

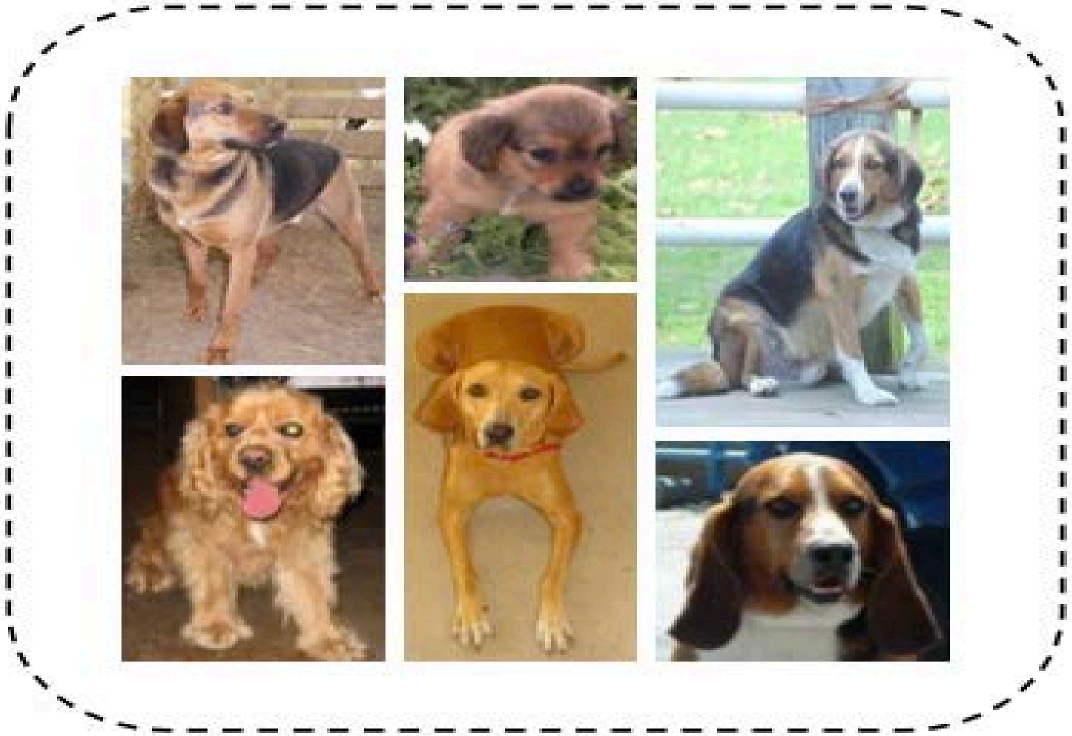
Classification Pipeline

Is it a cat or a dog?



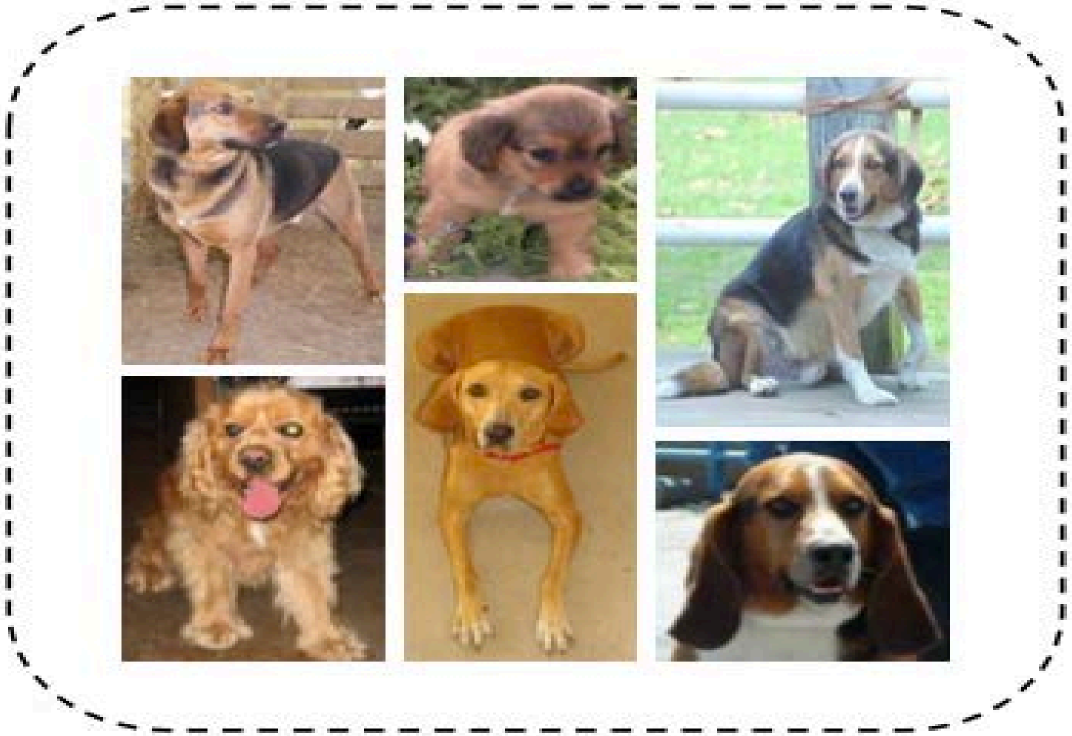
vs.

1. Gather data



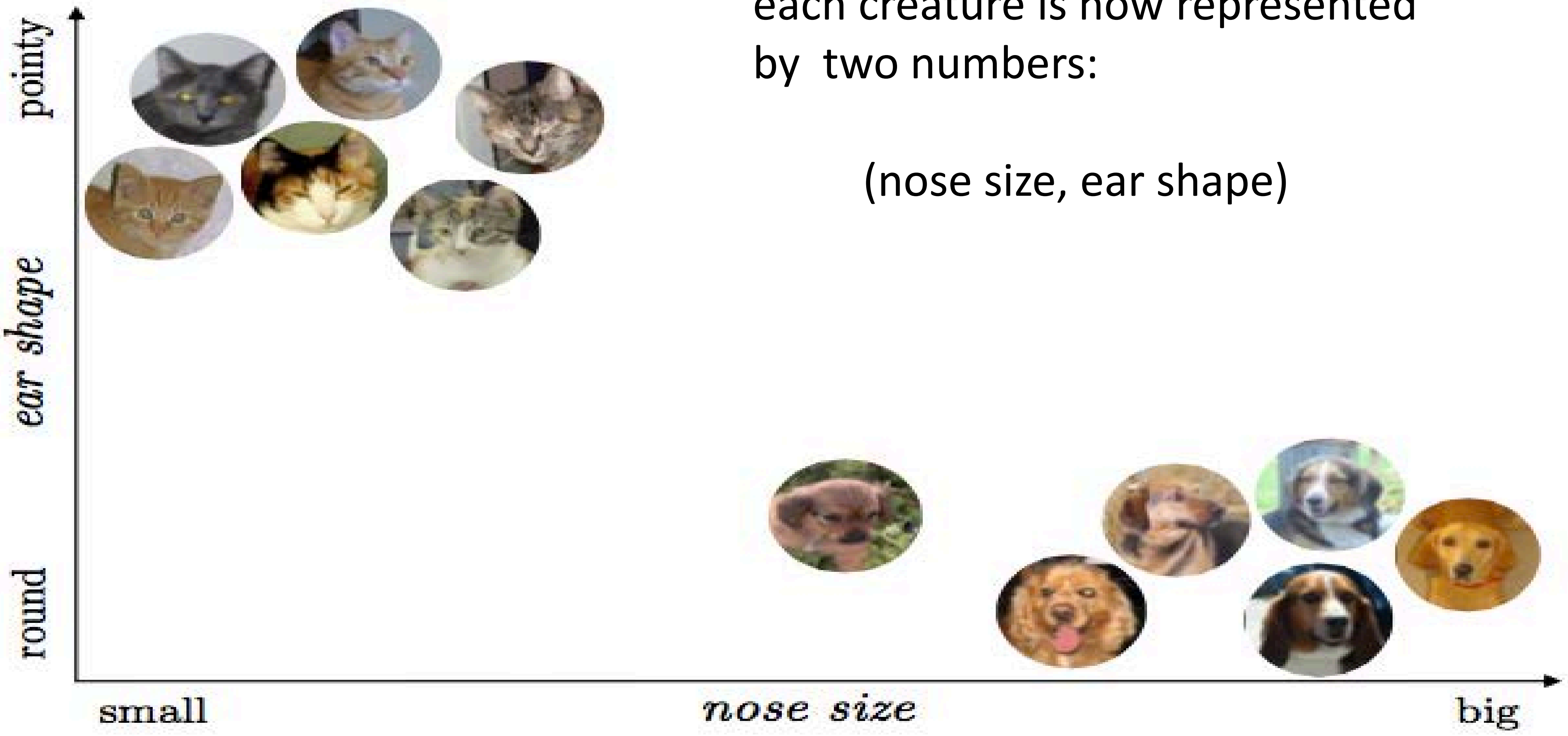
2. Extract features

(what distinguishes a cat from a dog?)



- cats have **small** noses and **pointy** ears
- dogs have **big** noses and **round** ears

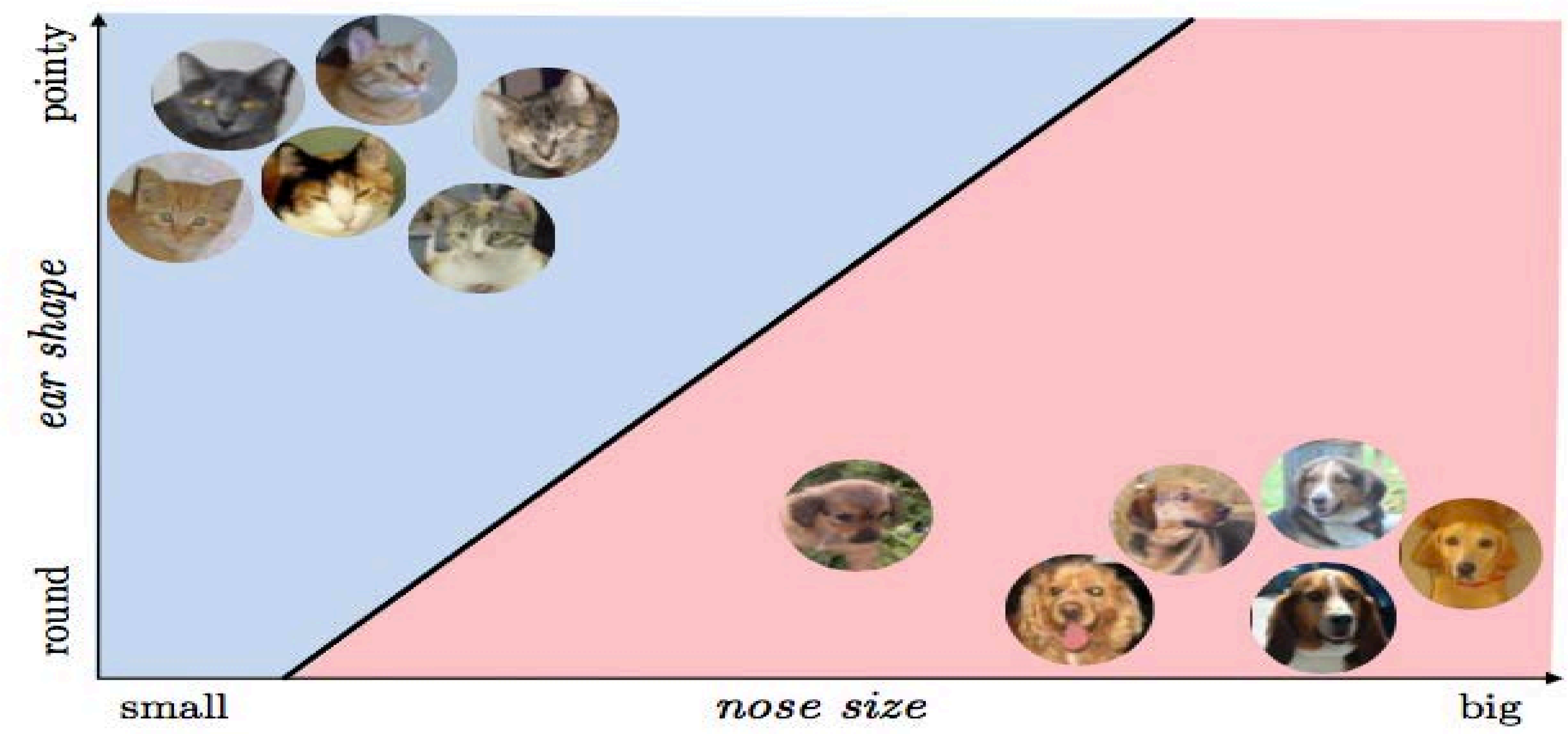
The *feature space*



each creature is now represented by two numbers:

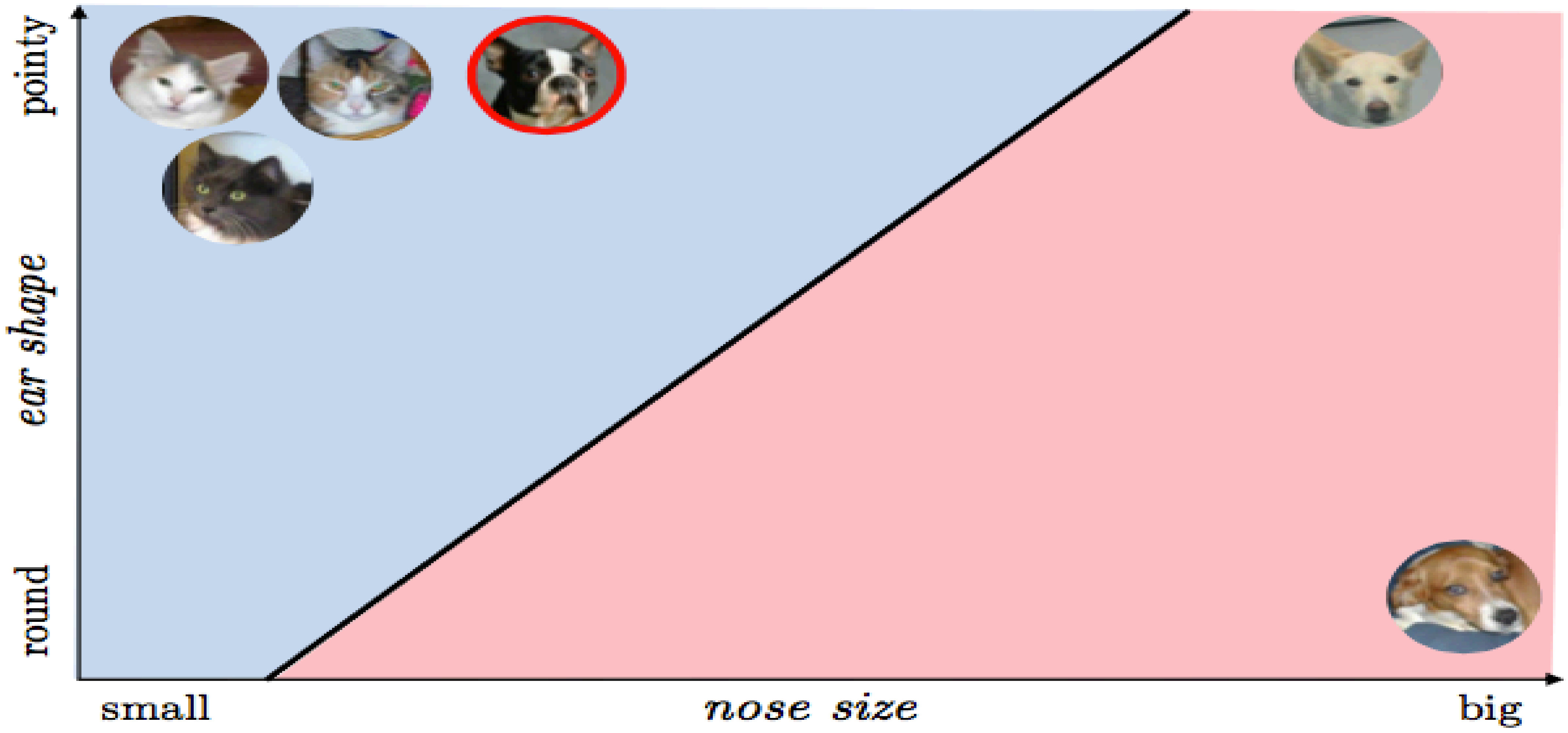
(nose size, ear shape)

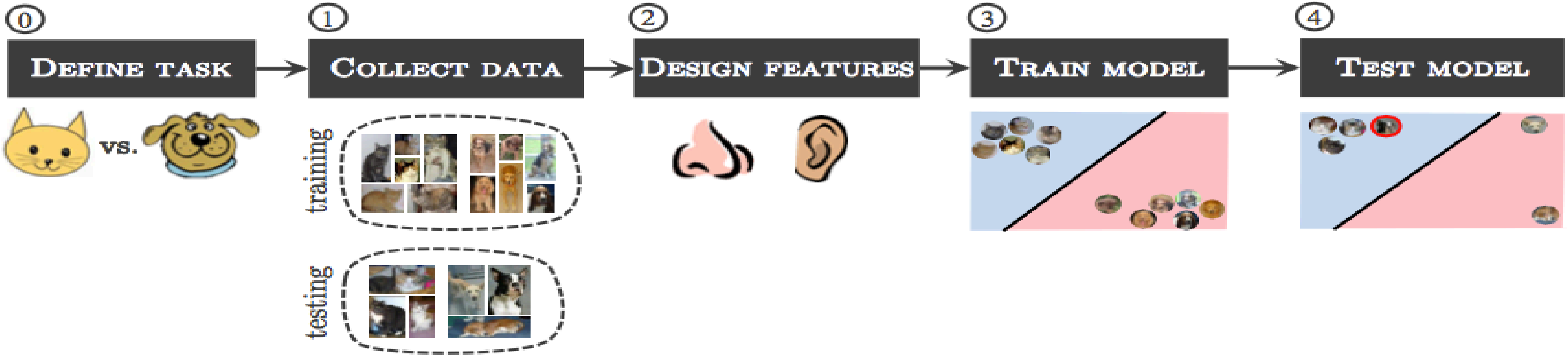
3. Train the model
(find best parameters via numerical optimization)



5. Test the model (on new data)

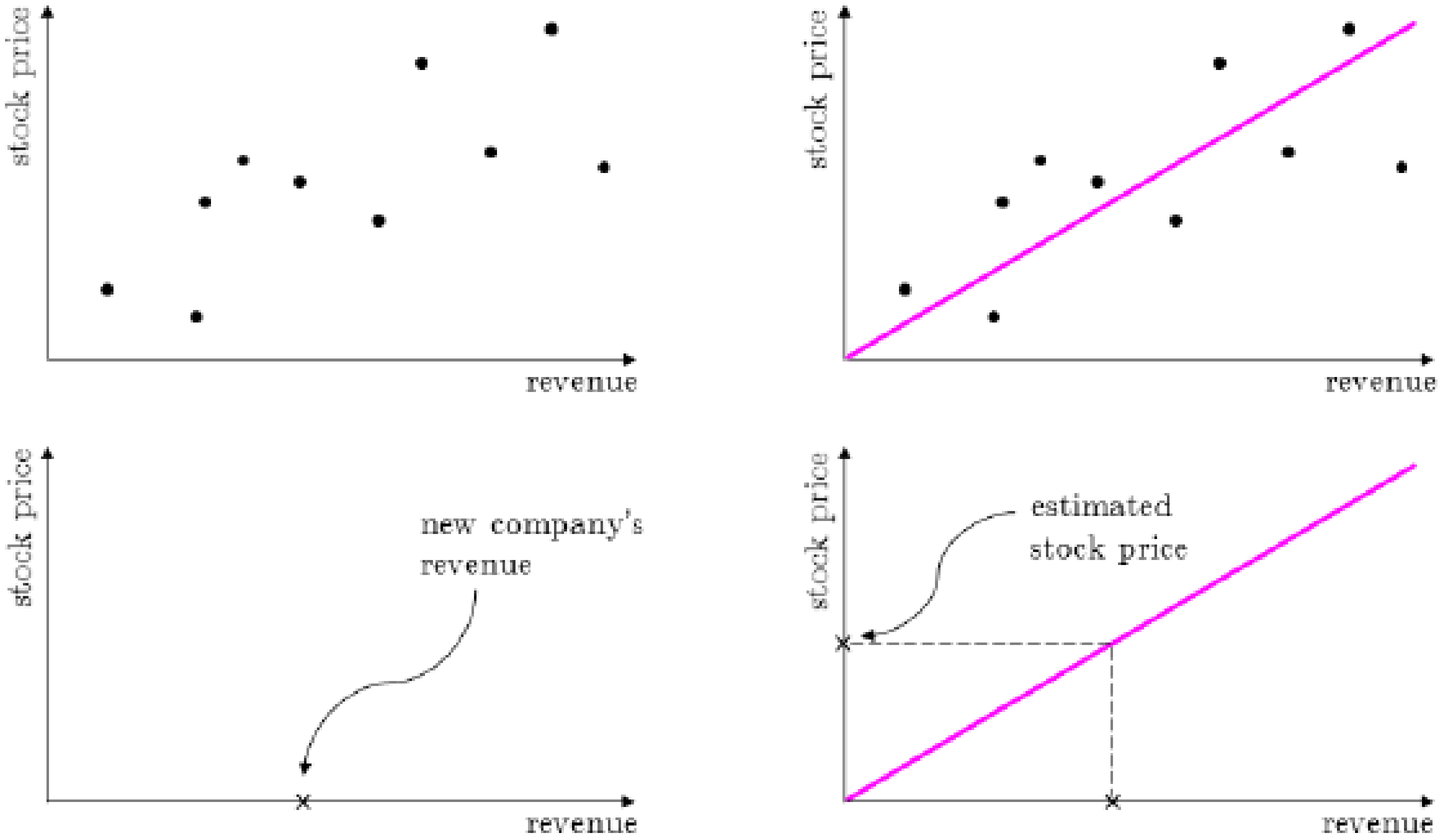
Meanwhile in the *feature space*...





0
Define task
vs.
1
Collect data
training
testing
2
Design features
3
Train model
4
Test model

Regression



stock price
revenue
stock price
revenue
stock price
new company's
revenue
revenue
stock price
estimated
stock price
revenue

Classification