EE 375/475 and Data_Sci 423
Machine Learning

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Outline

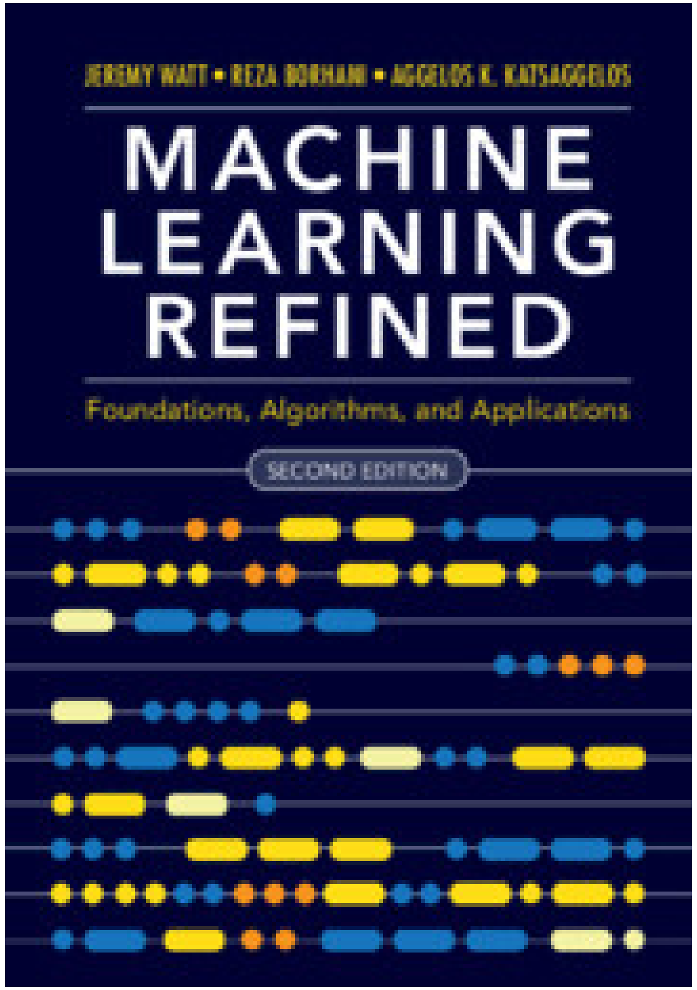
- Intro to Machine Learning and Numerical Optimization
- Regression
- Classification
- Function Approximation
- Bayesian Regression and Classification
- Matrix Factorization (K-Means, PCA, Recommender Systems,…)

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

AI/ML/DL

- **Artificial Intelligence (AI)** pertains to the theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, and decision-making.
- **Machine Learning (ML)** is an application of AI that provides systems the ability to automatically learn tasks and improve from experience without being explicitly programmed. It focuses on the development of computer programs that can process data in new ways and use it to learn for themselves.
- **Deep learning (DL)**, a subset of machine learning, utilizes a hierarchical level of artificial neural networks to carry out the process of machine learning (EE 435).
- Machine learning enables analysis of massive quantities of data (**big data**).

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 $f : R^n \to \{1, \cdots, k\}$
- 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 $f : R^n \to R$
- Transcription (optical character recognition, speech processing)
- Structured outputs (any task where the output exhibits important *relationships* 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 or precision (proportion of correct output over all outputs, i.e., TP/(TP+FP))
  - Recall or sensitivity (proportion of correct output over all correct outputs, i.e., TP/(TP+FN))
  - Specificity (TN/(TN+FP))
  - 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

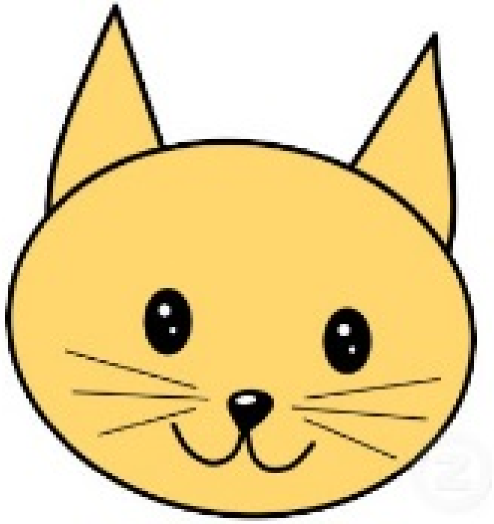
- Machine learning algorithms can be broadly categorized as ***unsupervised*** or ***supervised***
- Unsupervised learning algorithms experience a dataset containing many features, then learn useful properties of the structure of this dataset
- Supervised learning algorithms experience a dataset containing 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 (EE 373/473 Deep Reinforcement Learning)

Classification Pipeline

Is it a cat or a dog?



vs.

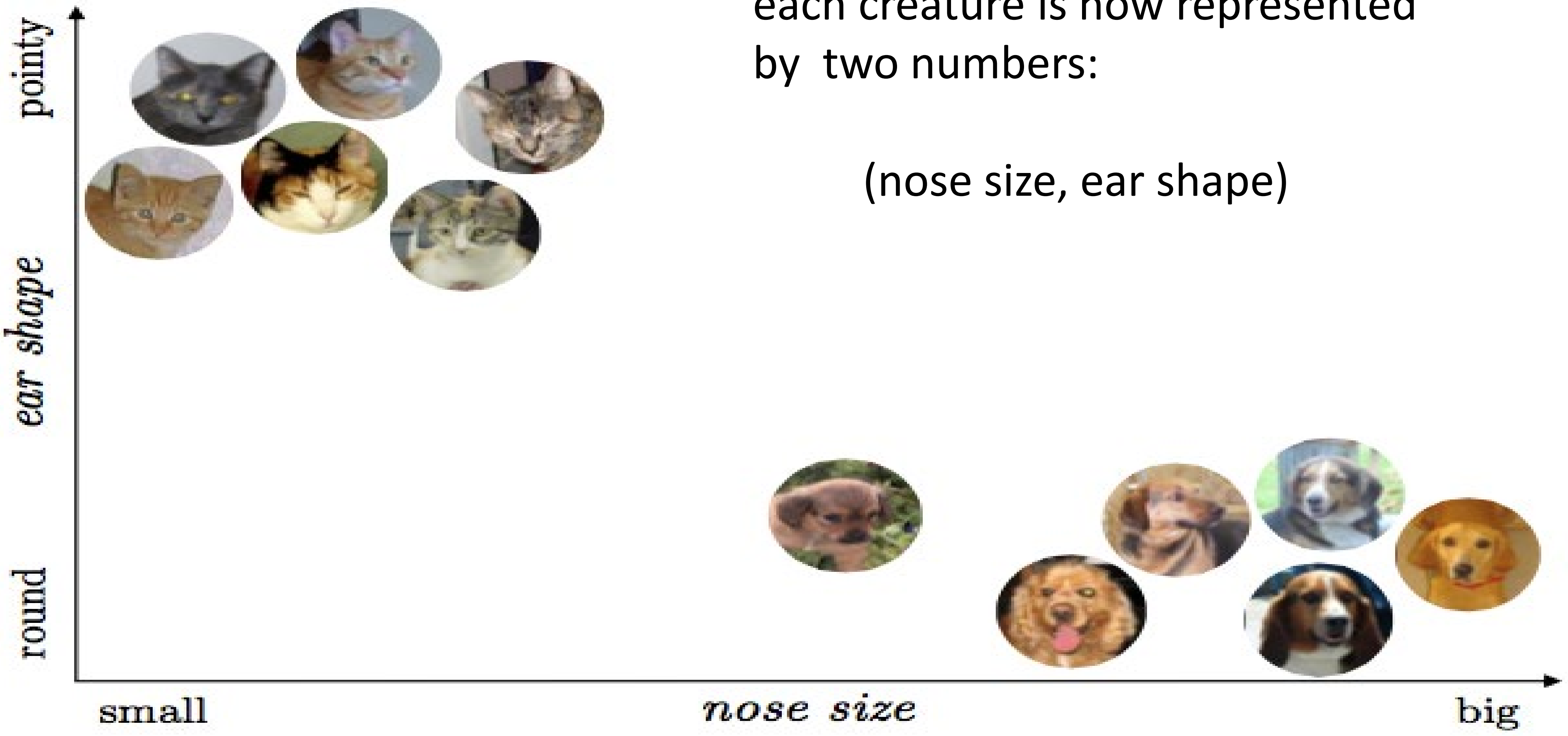
1. Gather data

2. Extract features

(what distinguishes a cat from a dog?)

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

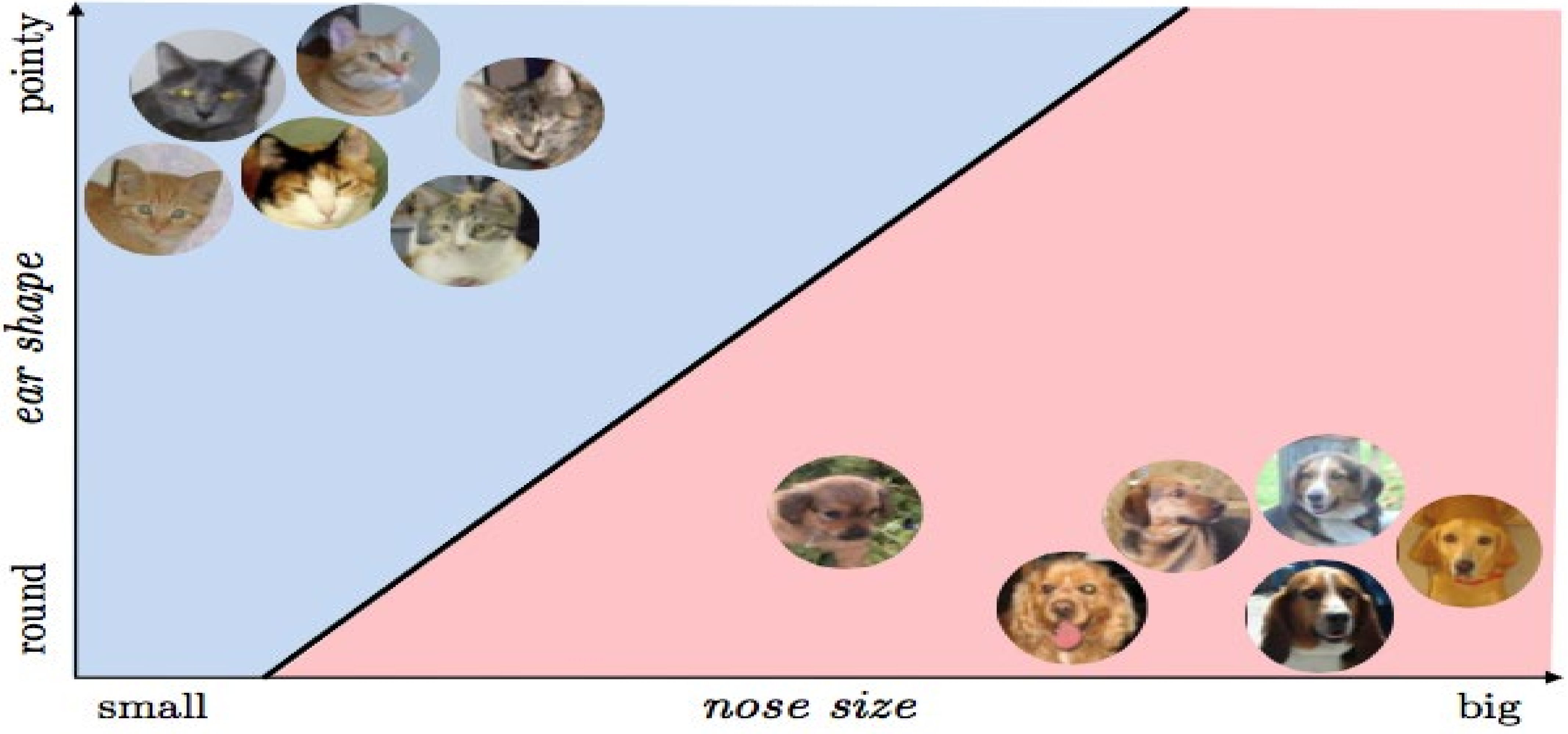
The *feature space*



each creature is now represented by two numbers:

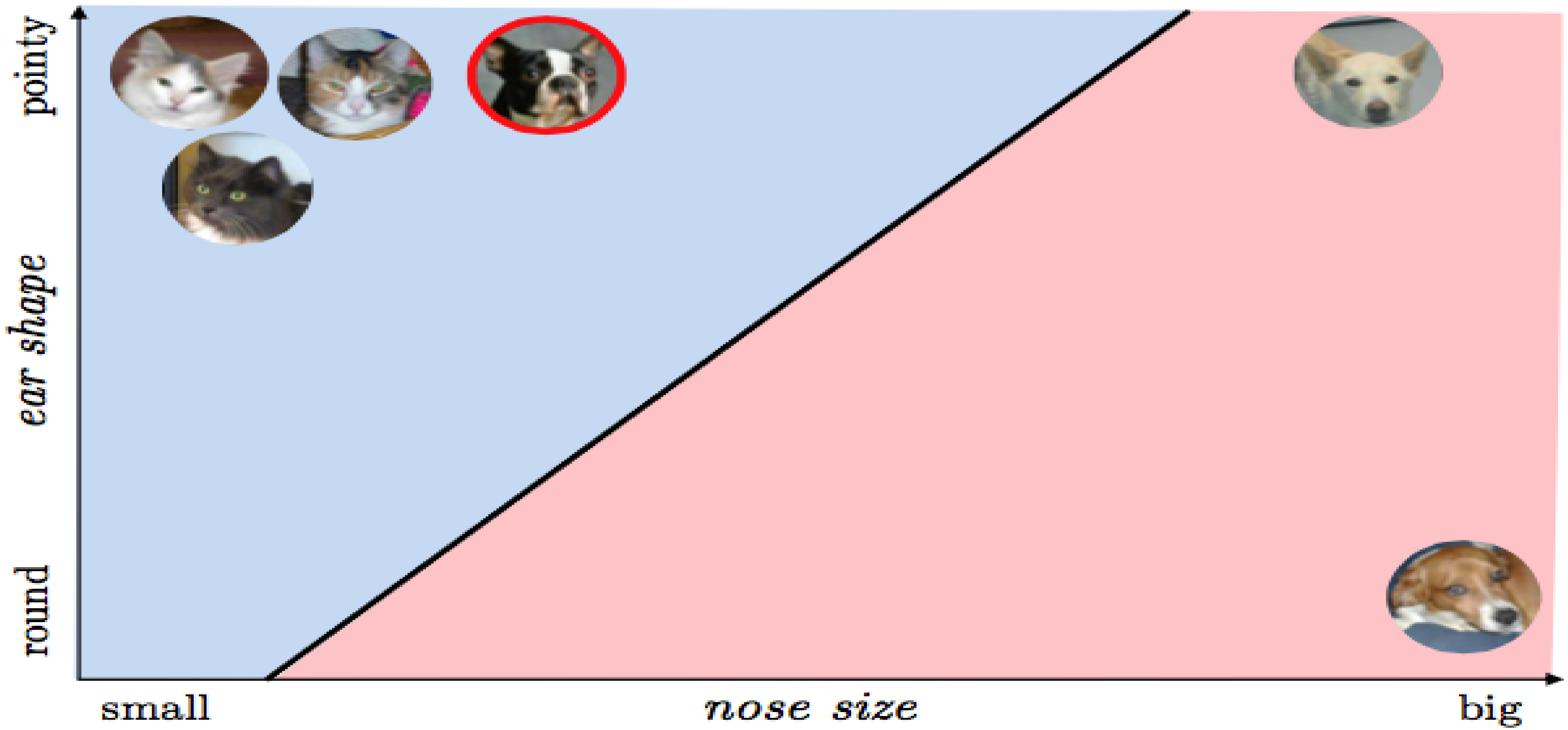
(nose size, ear shape)

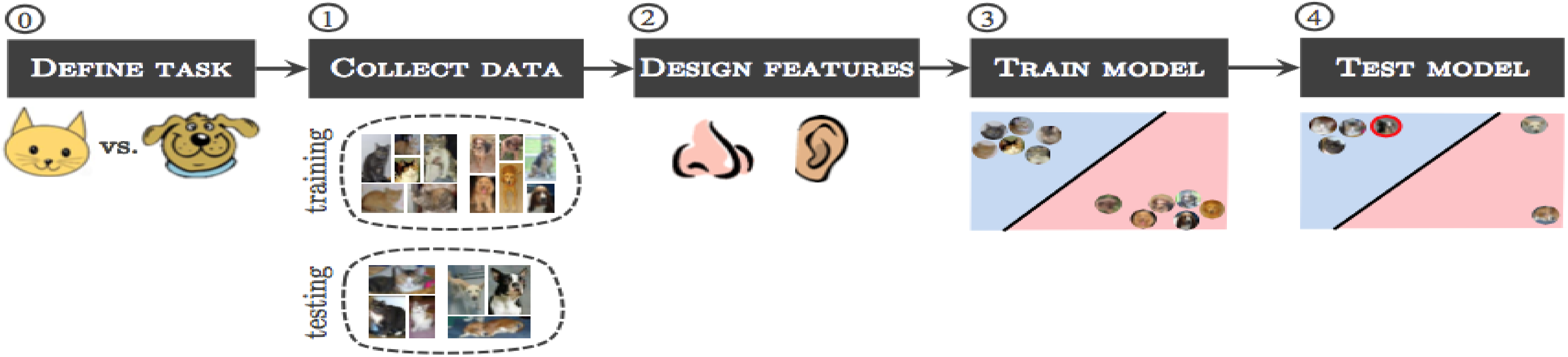
3. Train the model
(find best parameters via numerical optimization)



5. Test the model (on new data)

Meanwhile in the *feature space*...

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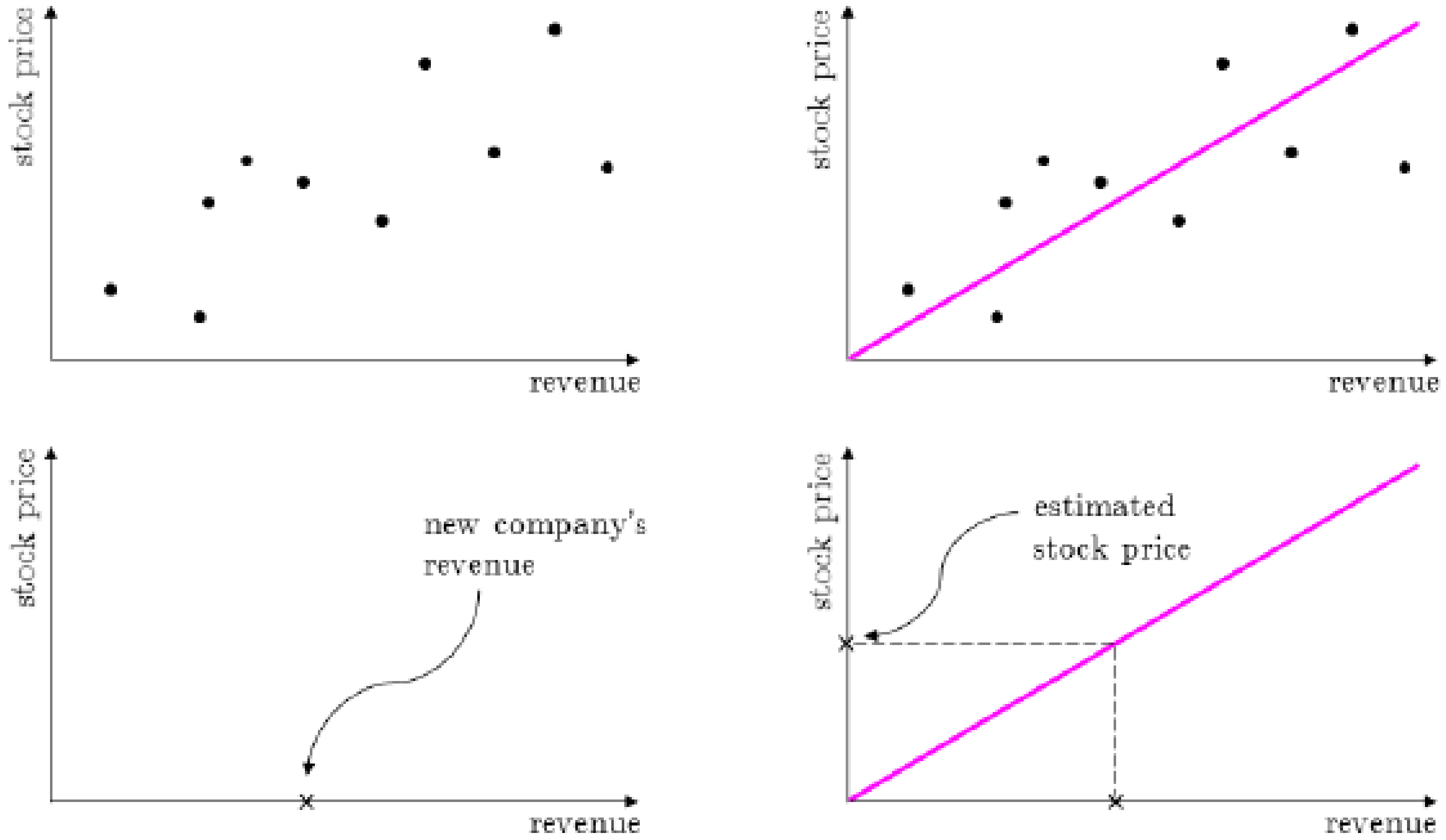
Define task
vs.
1
Collect data
training
testing
2
Design features
3
Train model
4
Test model

Regression



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

Classification