COMP3204/COMP6223: Computer Vision

Machine learning for pattern recognition

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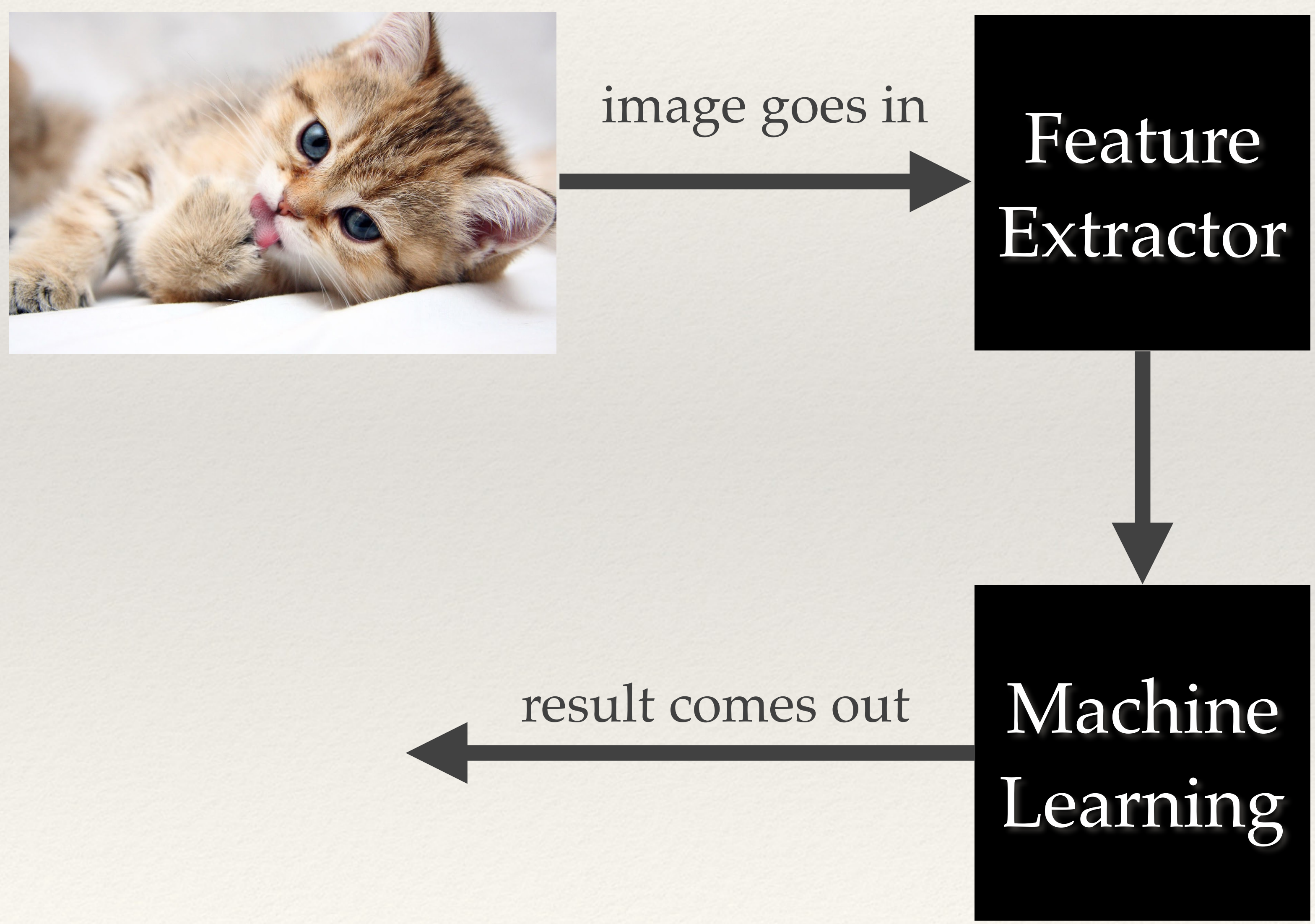
RETURN TO D-STATION.

- Recognising patterns is a large part of computer vision
  - i.e. recognising text, people, objects, …
- Obviously there’s a lot of overlap with intelligent algorithms, machine learning and AI.
- This lecture will cover (recap?) some of the fundamentals of machine learning and introduce how you connect arrays of pixels to machine learning algorithms.

Feature spaces

Many computer vision applications involving machine learning take the following form:



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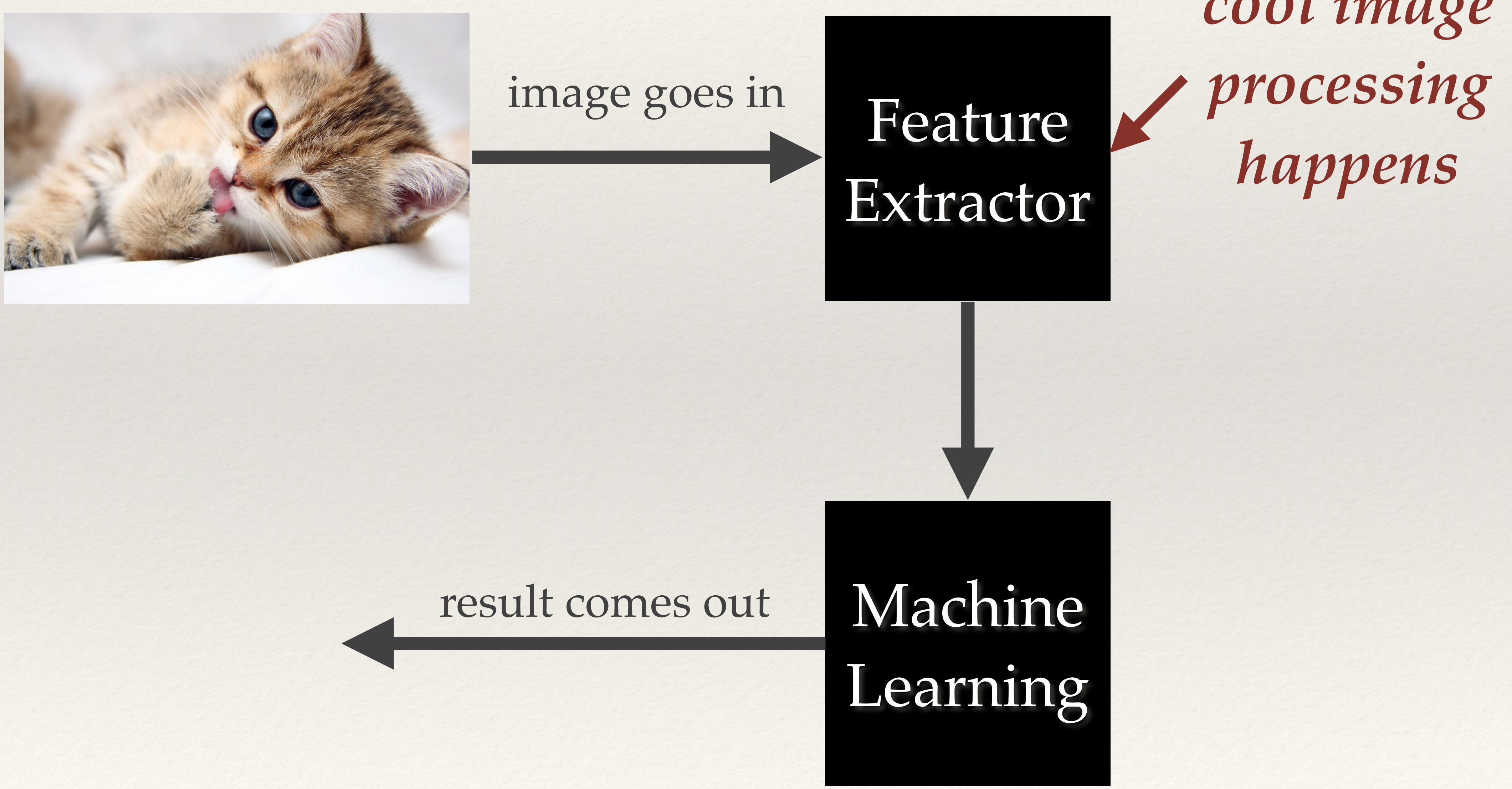

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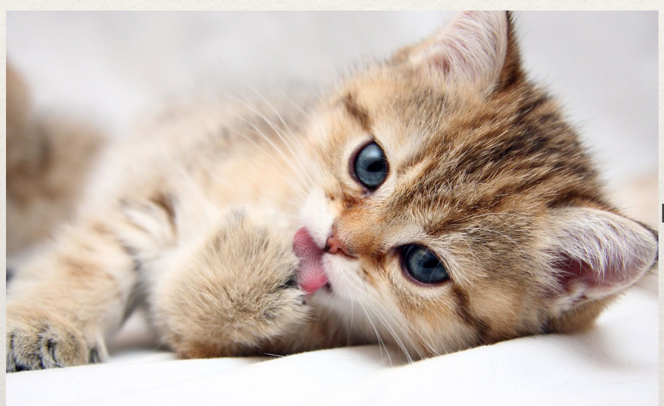

image goes in

Feature Extractor

feature extractors make featurevectors from images

Machine Learning

result comes out

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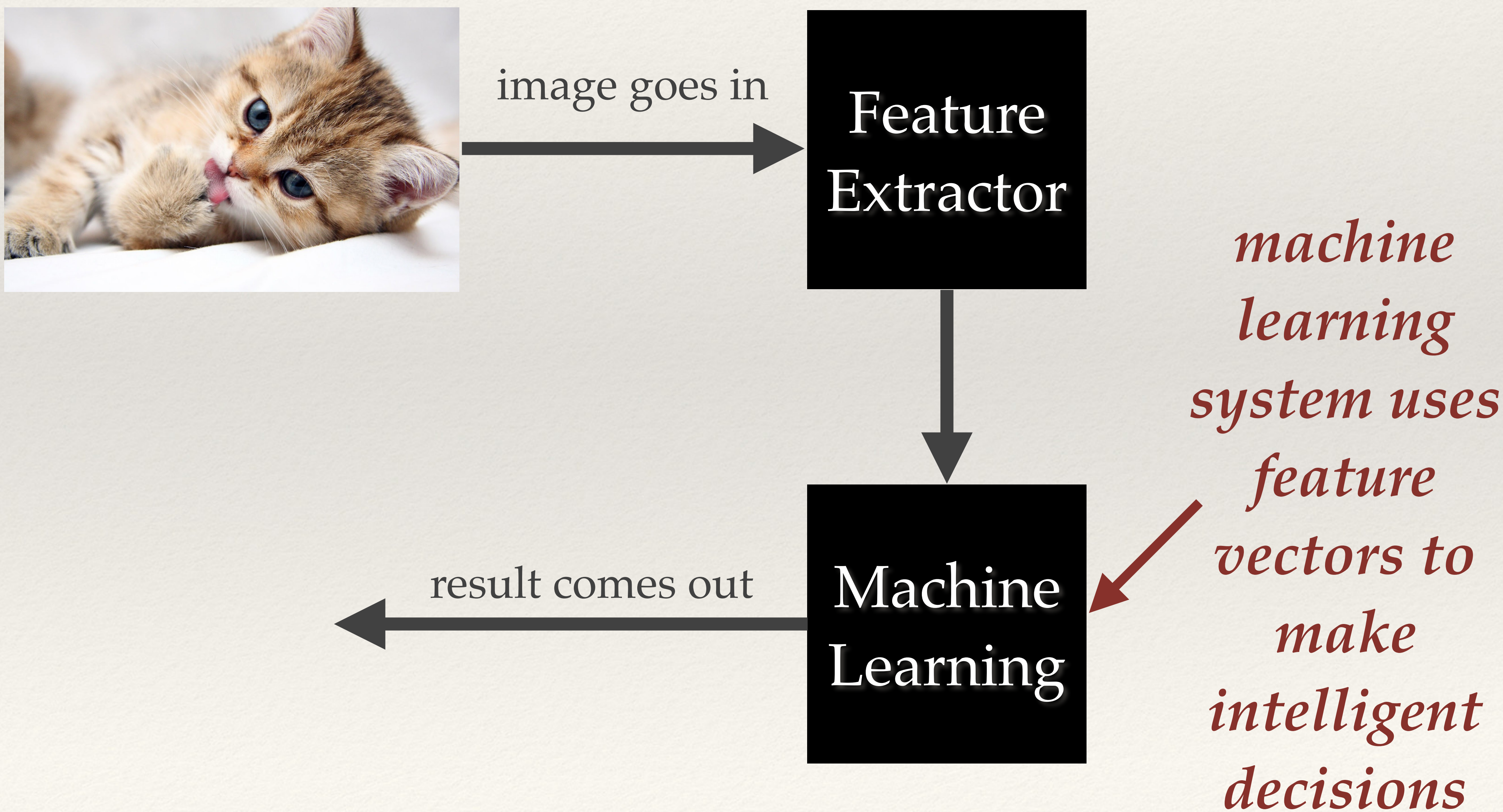


Key terminology

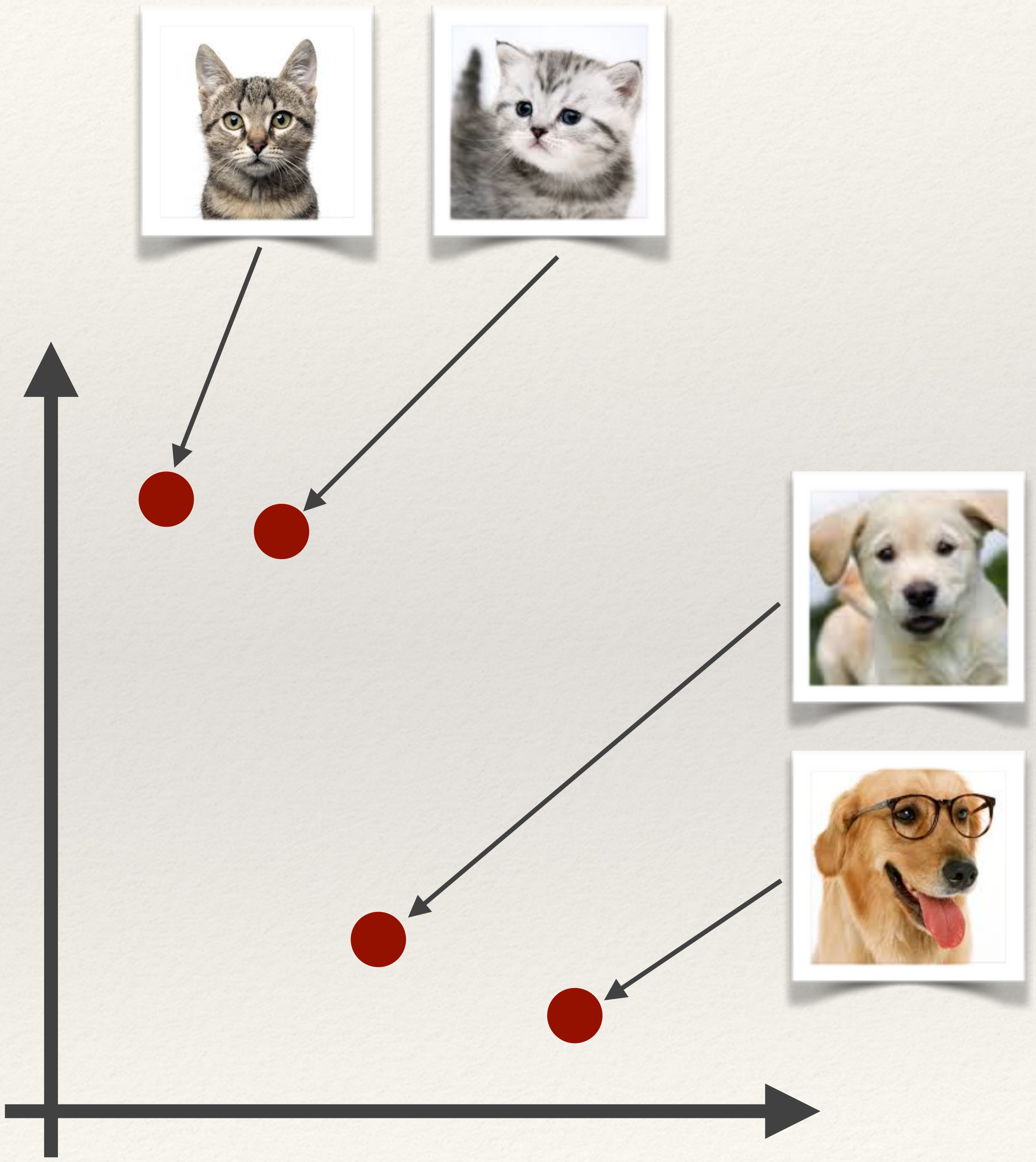
- **featurevector**: a mathematical vector
  - just a list of (usually Real) numbers
  - has a fixed number of **elements** in it
    - The number of elements is the **dimensionality** of the vector
  - represents a **point** in a **featurespace** or equally a **direction** in the featurespace
  - the **dimensionality of a featurespace** is the dimensionality of every vector within it
    - vectors of differing dimensionality can’t exist in the same featurespace

Demo: a really simple feature extractor

Distance and similarity

Distances in featurespace

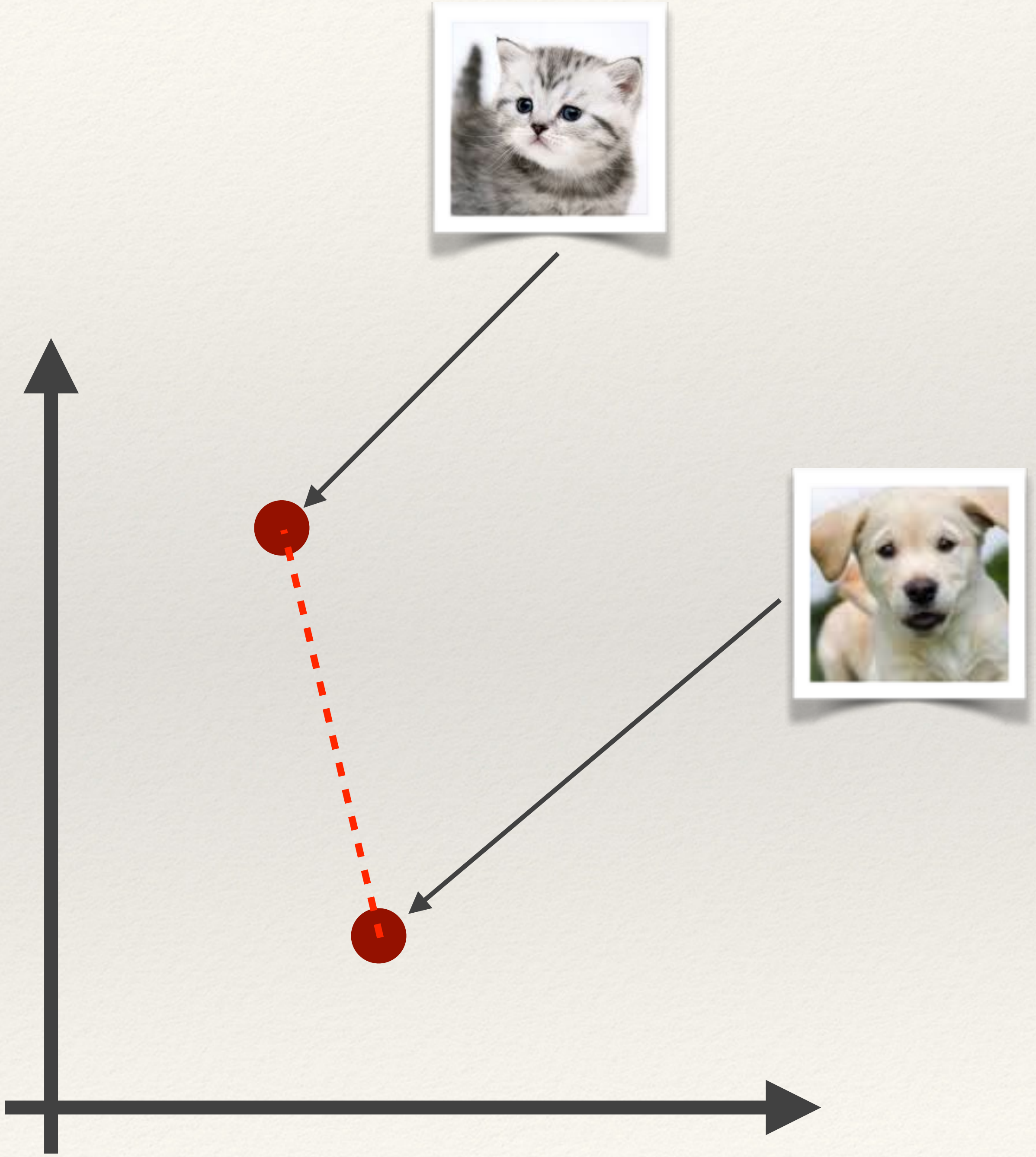
- Feature extractors are often defined so that they produce vectors that are *close* together for *similar* inputs
    - Closeness of two vectors can be computed in the feature space by measuring a distance between the vectors.



Euclidean distance (*L2 distance*)

- L2 distance is the most intuitive distance…
  - The straight-line distance between two points
  - Computed via an extension of Pythagoras theorem to *n* dimensions:

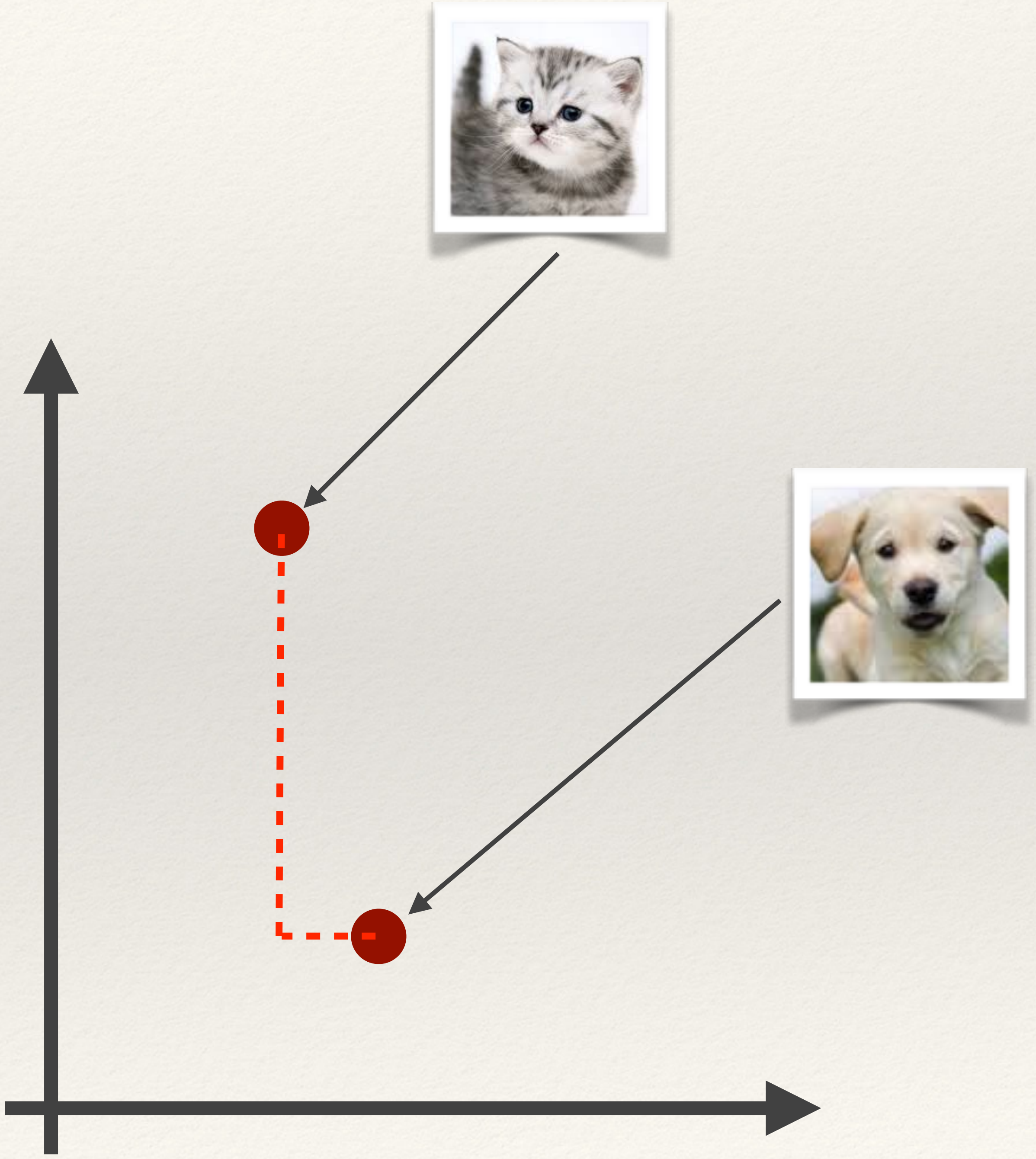
$$D_2(p,q) = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} = \|p-q\| = \sqrt{(p-q)\cdot(p-q)}$$



L1 distance (*aka Taxicab/Manhattan*)

- L1 distance is computed along paths parallel to the axes of the space:

$$D_1(p,q) = \sum_{i=1}^{n} |p_i - q_i| = \|p - q\|_1$$

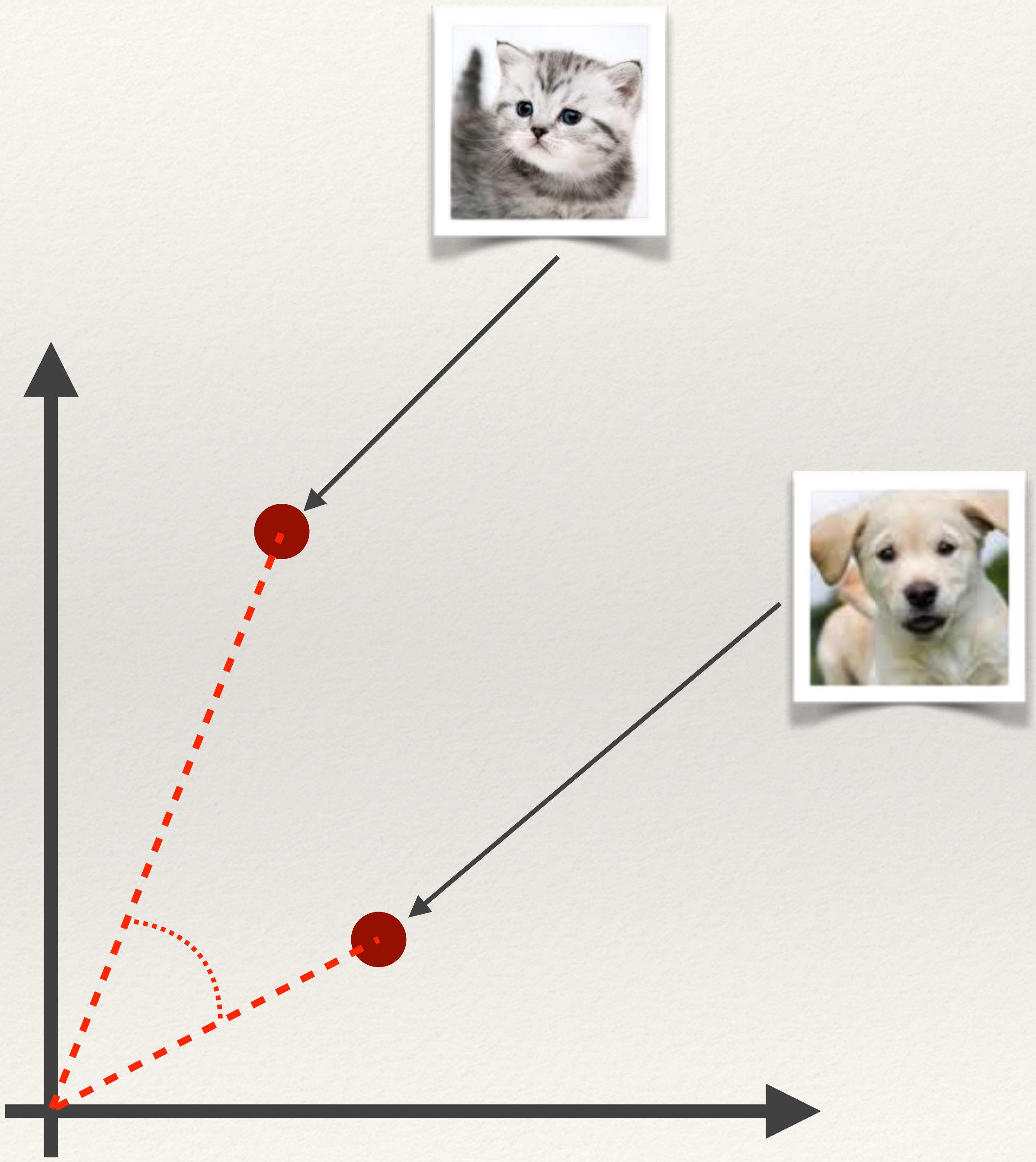


Cosine Similarity

- Cosine similarity measures the cosine of the angle between two vectors
  - **It is not a distance!**

$$cos(\theta) = \frac{p.q}{||p|| \, ||q||} = \frac{\sum_{i=1}^{n} p_i q_i}{\sqrt{\sum_{i=1}^{n} p_i^2} \sqrt{\sum_{i=1}^{n} q_i^2}}$$

  - Useful if you don't care about the relative length of the vectors



Choosing good featurevector representations for machine-learning

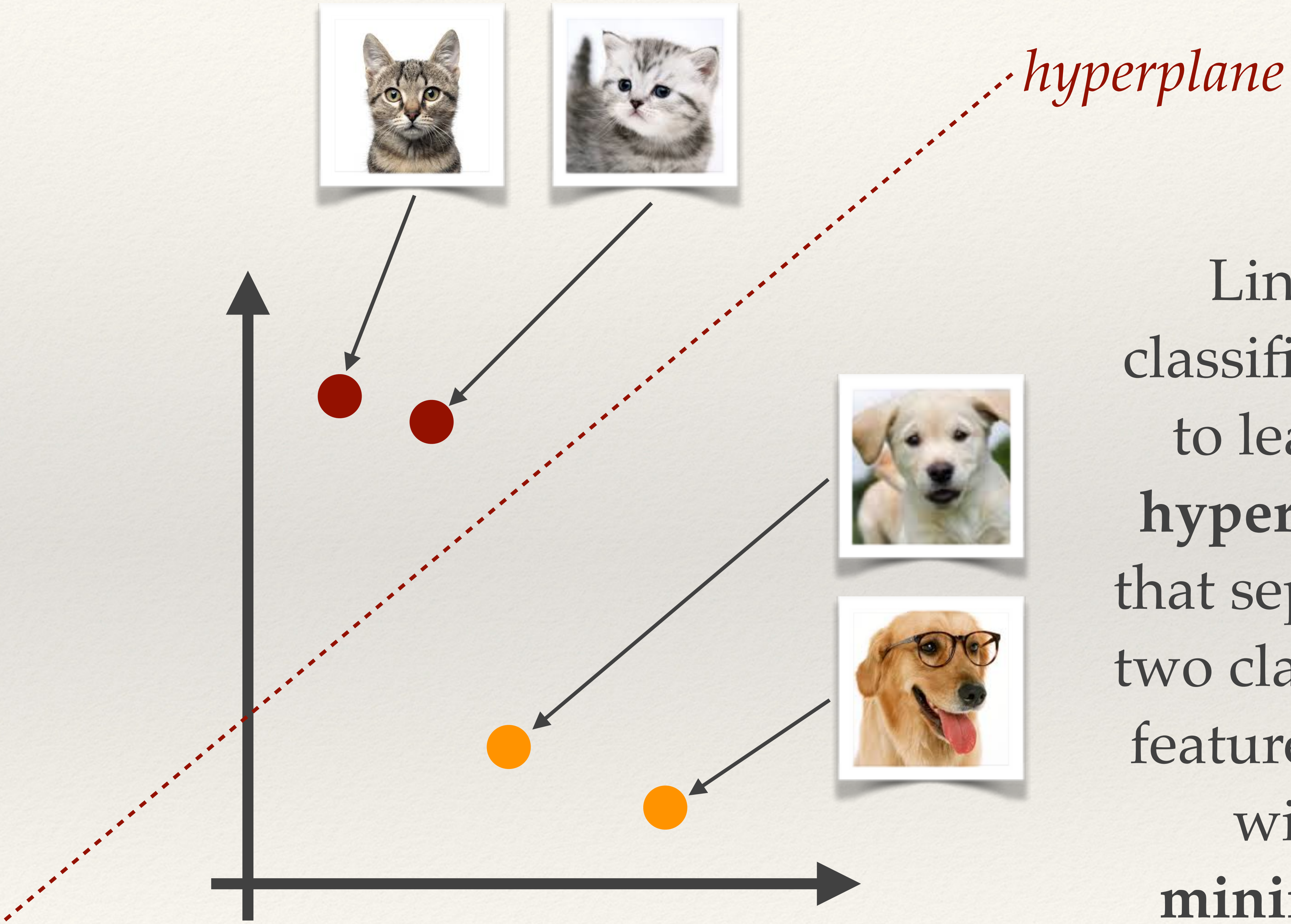
- Choose features which allow to distinguish objects or classes of interest
    - Similar within classes
    - Different between classes
- Keep number of features small
    - Machine-learning can get more difficult as dimensionality of featurespace gets large

Supervised Machine Learning: *Classification*

- **Classification** is the process of assigning a **class label** to an object (typically represented by a vector in a feature space).
- A **supervised machine-learning algorithm** uses a set of pre-labelled *training data* to learn how to assign class labels to vectors (and the corresponding objects).
    - A **binary** classifier only has two classes
    - A **multiclass** classifier has many classes.

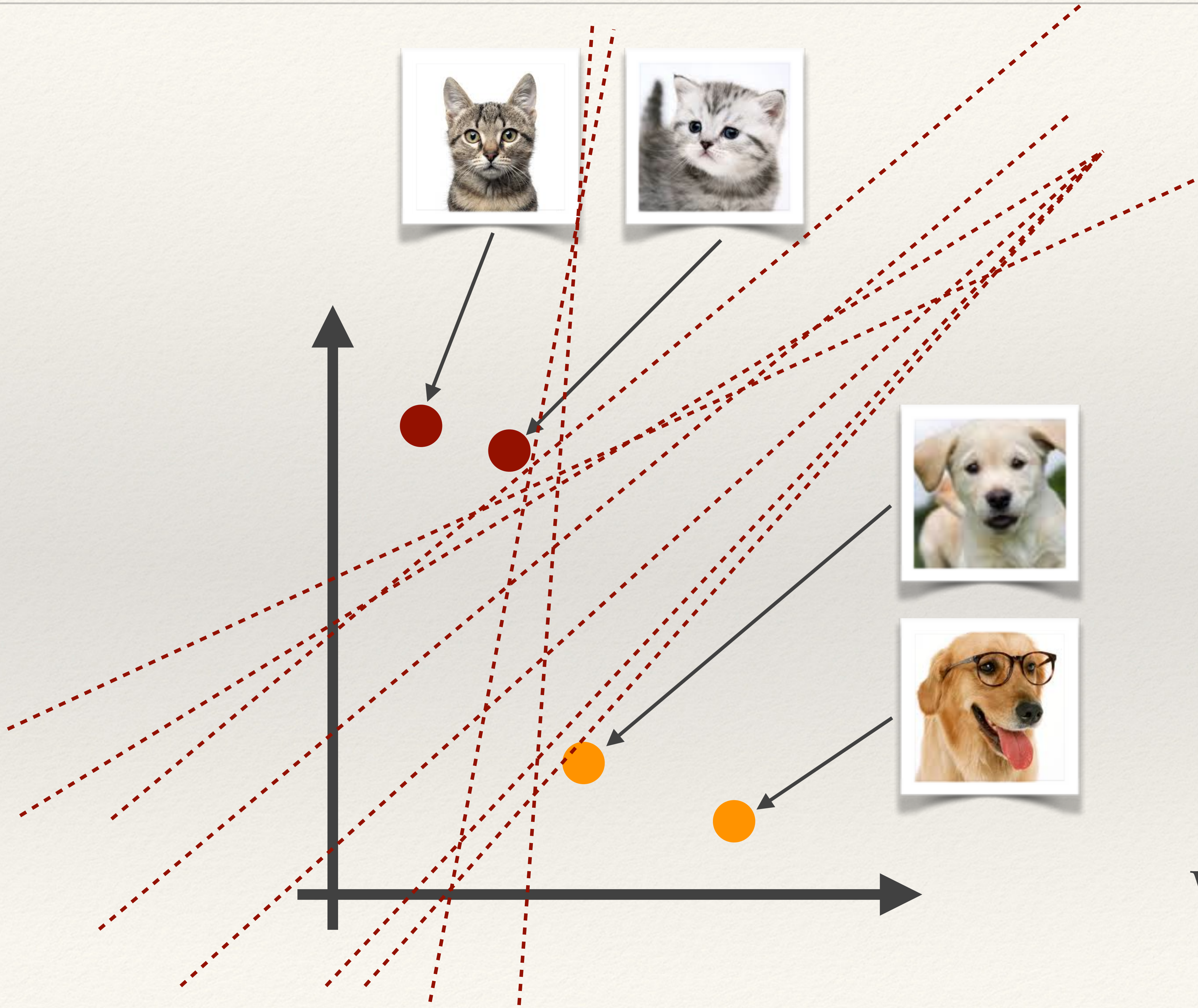
Cat or Dog?

Linear classifiers



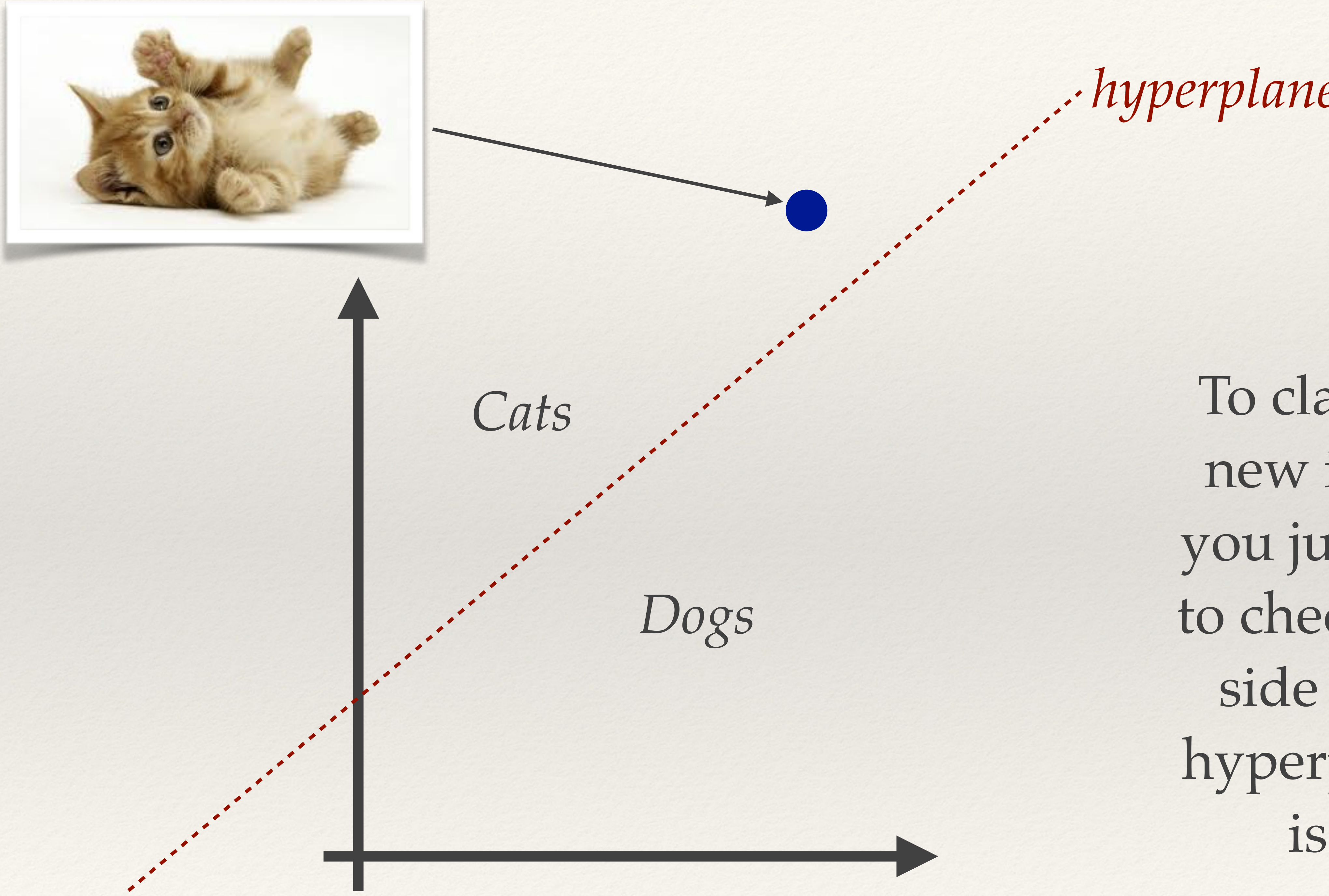
Linear classifiers try to learn a **hyperplane** that separates two classes in featurespace with **minimum error**

Linear classifiers



Lots of hyperplanes to choose from… different linear classification algorithms apply differing constraints when learning the classifier

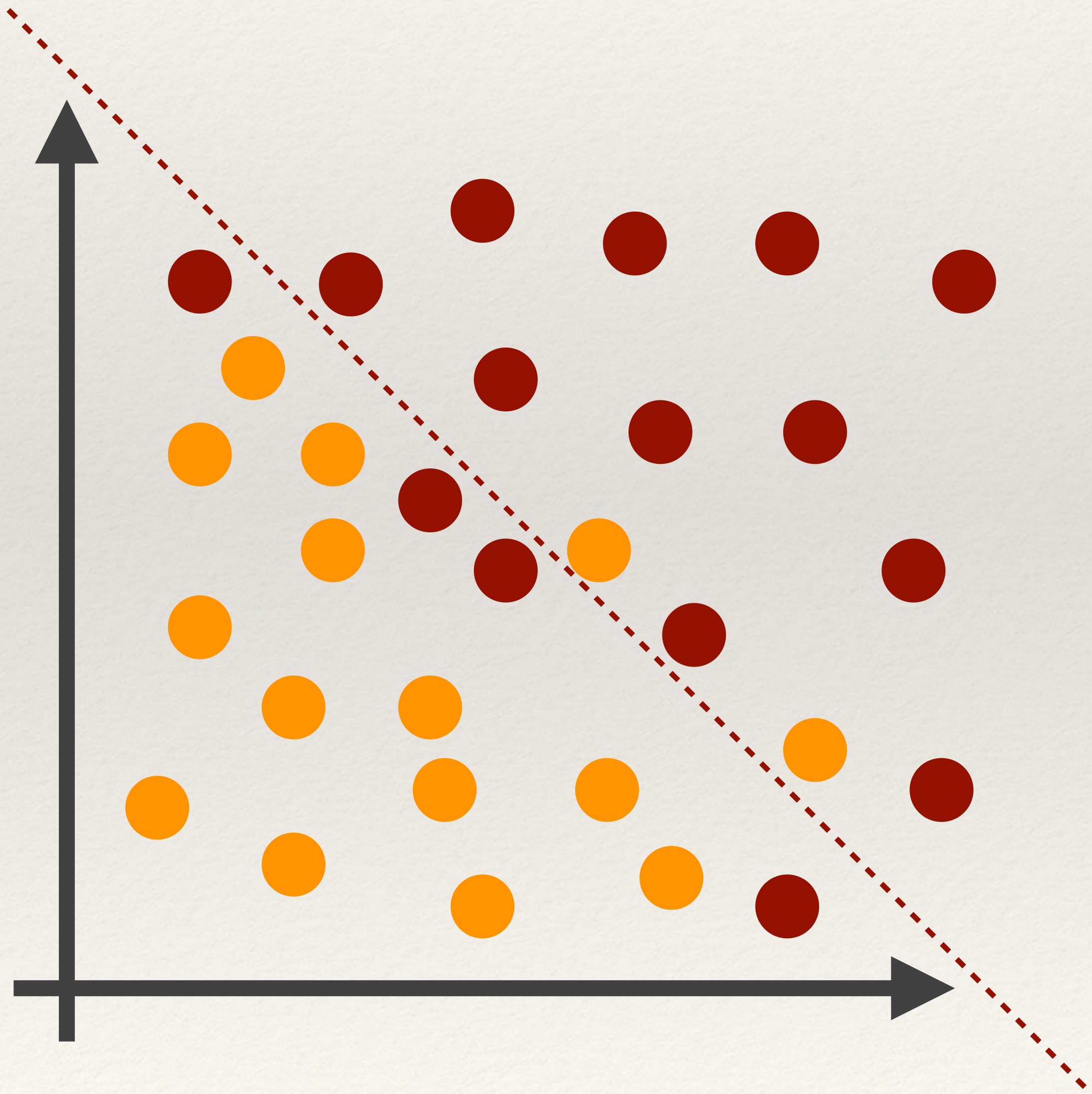
Linear classifiers



To classify a new image, you just need to check what side of the hyperplane it is on

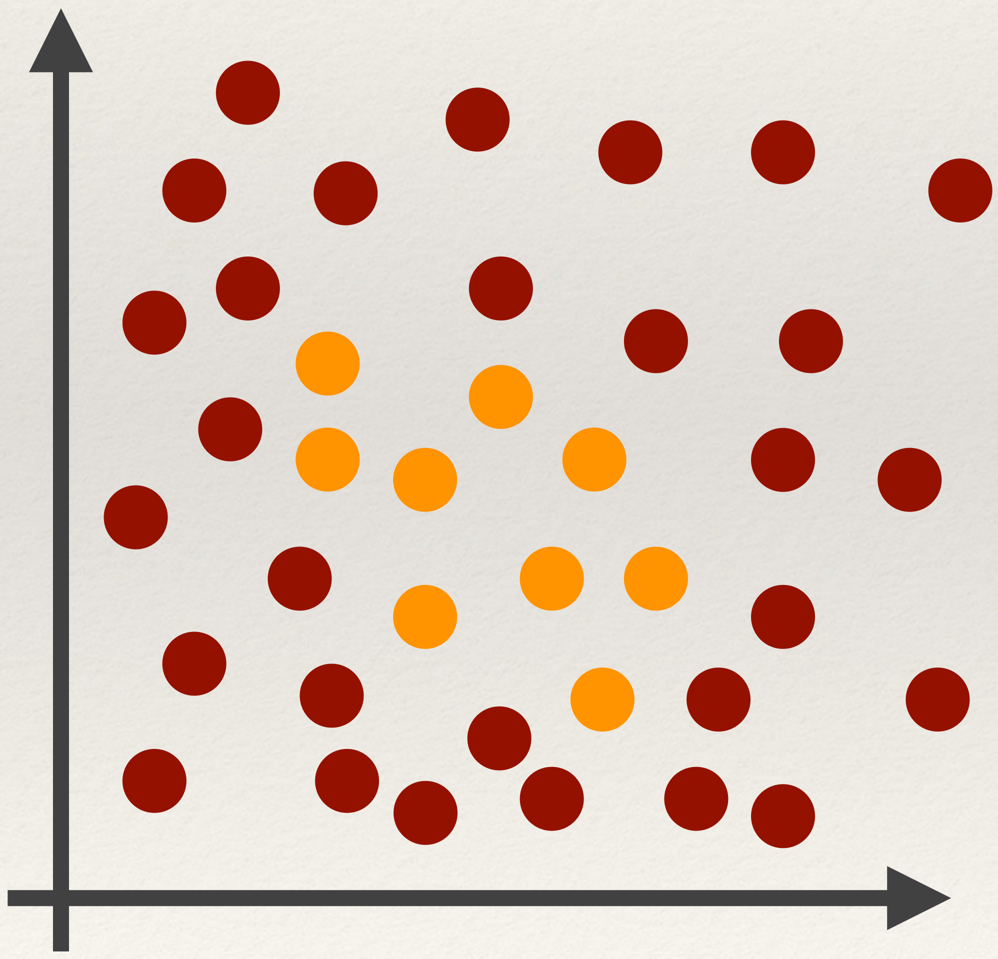
Demo: perceptron linear classifier

Non-linear binary classifiers



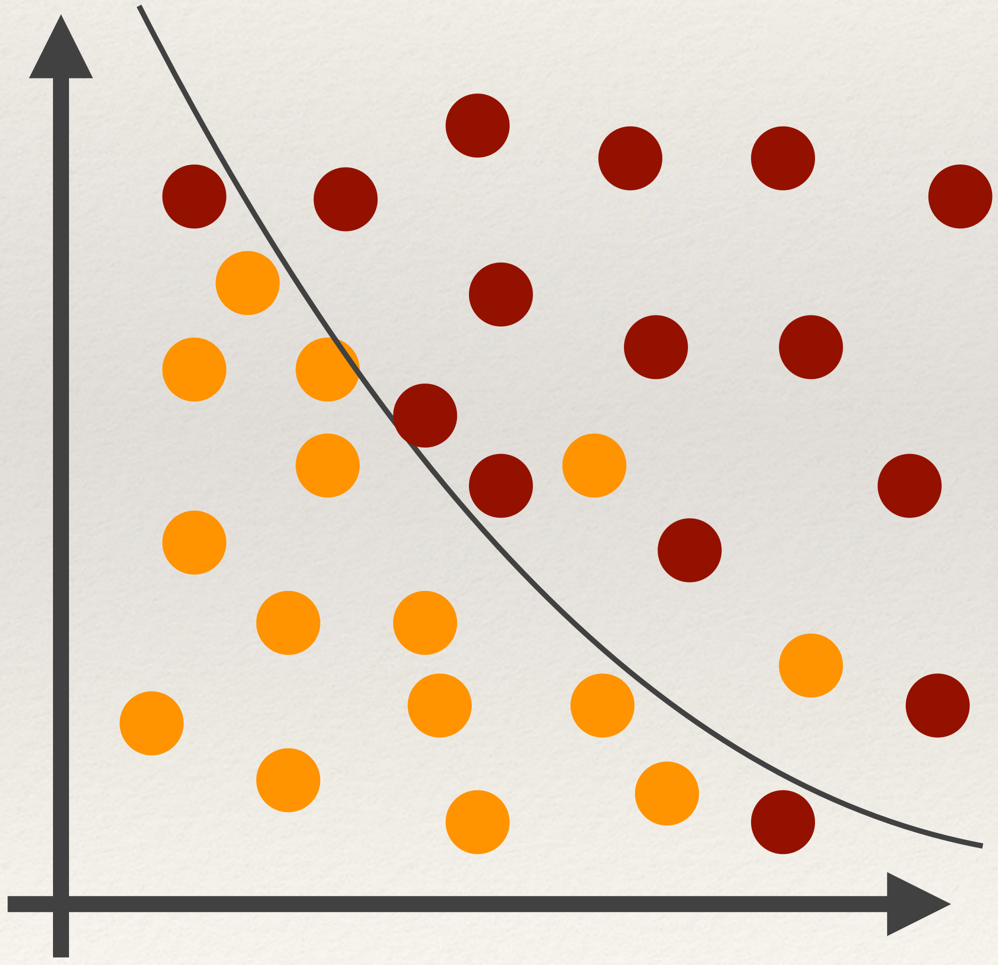
Linear classifiers work best when the data is linearly separable…

Non-linear binary classifiers



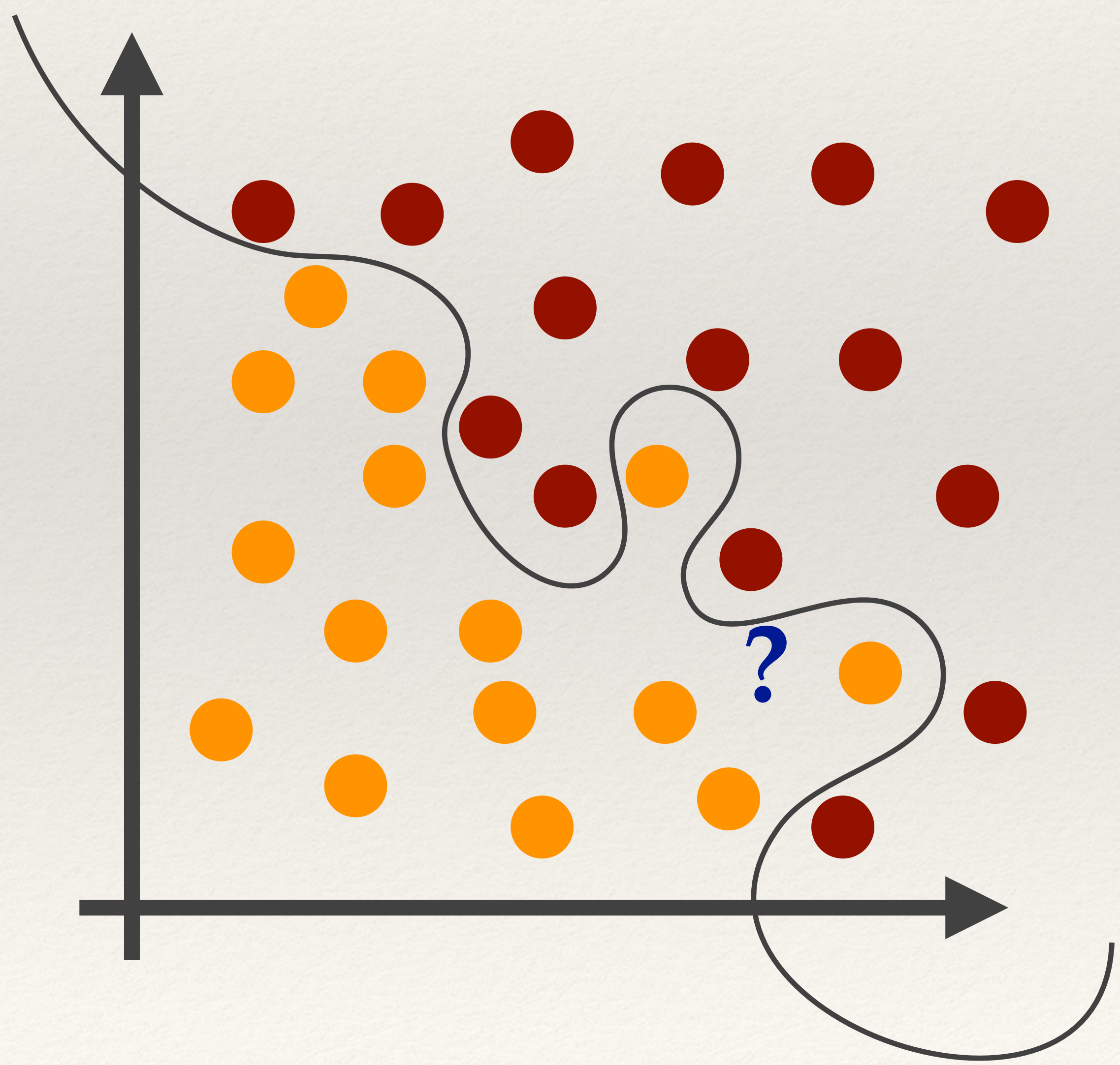
No hope for a linear classifier!

Non-linear binary classifiers



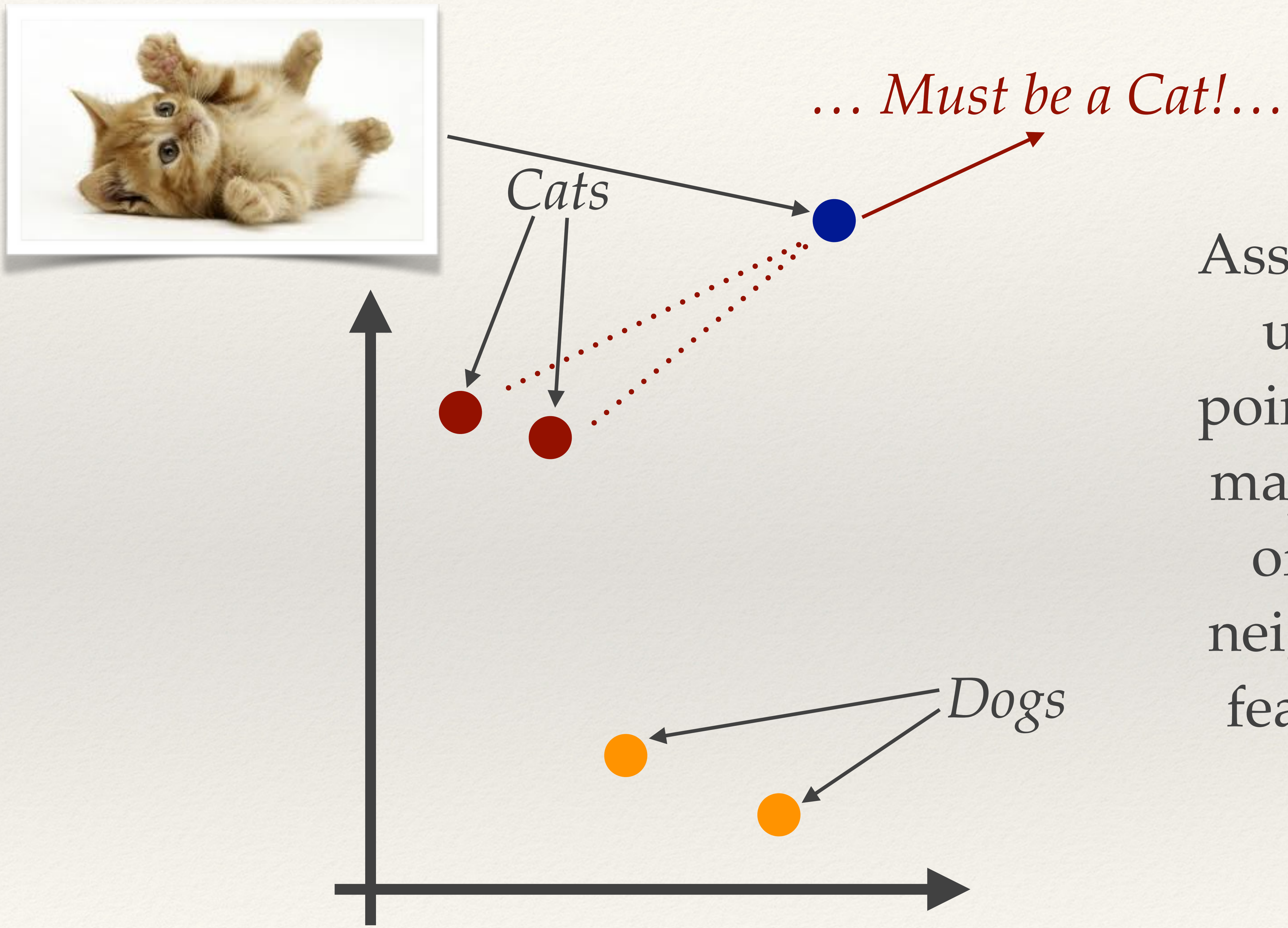
Non-linear binary classifiers, such as **Kernel Support Vector Machines** learn non-linear decision boundaries

Non-linear binary classifiers



Have to be careful… you might lose generality by overfitting

Multiclass classifiers: KNN



Assign class of unknown point based on majority class of *closest K* neighbours in featurespace

Demo: KNN Classification

KNN Problems

- Computationally expensive if there are:
  - Lots of training examples
  - Many dimensions

Multiclass linear classifiers

- A linear classifier is by definition binary
  - So, how can we solve multiclass problems with linear classifiers?
    - One versus All (OvA)/One versus Rest (OvR)
      - one classifier per class
    - One versus One (OvO)
      - K (K – 1) / 2 classifiers

Unsupervised Machine Learning:
Clustering

- Clustering aims to group data without any prior knowledge of what the groups should look like or contain.
- In terms of featurevectors, items with similar vectors should be grouped together by a clustering operation.

- Some clustering operations create overlapping groups; for now we're only interested in disjoint clustering methods that assign an item to a single group.

K-Means Clustering

- K-Means is a classic featurespace clustering algorithm for grouping data into *K* groups with each group represented by a *centroid*:
  - The value of K is chosen
  - K initial cluster centres are chosen
  - Then the following process is performed iteratively until the centroids don’t move between iterations:
    - Each point is assigned to its closest centroid
    - The centroid is recomputed as the mean of all the points assigned to it. If the centroid has no points assigned it is randomly re-initialised to a new point.
  - The final clusters are created by assigning all points to their nearest centroid.

Demo: K-Means Clustering

Summary

- Extracting features is key part of computer vision
    - Typically, these are numerical vectors that can be used with machine-learning techniques.
    - Featurevectors can be compared by measuring distance
- Classification learns what class to assign a feature to.
- Clustering groups similar features.