

Lecture 1 Mathematical

Foundations of Machine Learning

Elements of Machine Learning

Imagine we want to take a photograph of a face and determine whether the person is smiling or not.

Key idea: we represent whether face is smiling with a model - a mathematical description of the data

Basis steps:

① Collect raw data - e.g. photographs of faces

② preprocessing - change the data to simplify subsequent operations without losing relevant information - e.g. crop images to only contain one face
center face

resize so all images have same # pixels

③ Feature extraction - reduce raw data by extracting features or properties

relevant to model (This step is often unnecessary in modern image recognition systems based on deep neural nets)

- e.g. distances between pairs of facial landmarks

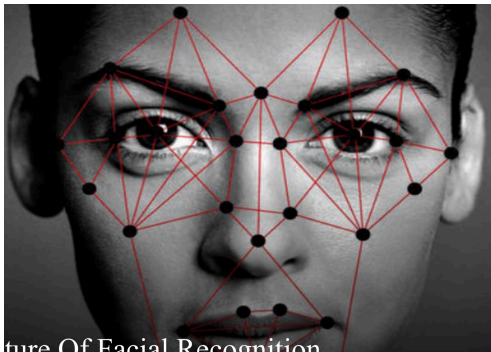


Figure Of Facial Recognition

④ generate training samples = large collection of examples we can use to learn a model

(\underline{x}_i, y_i) for $i=1, \dots, n \Rightarrow n = \#$ training samples

$y_i = i^{\text{th}}$ sample's label

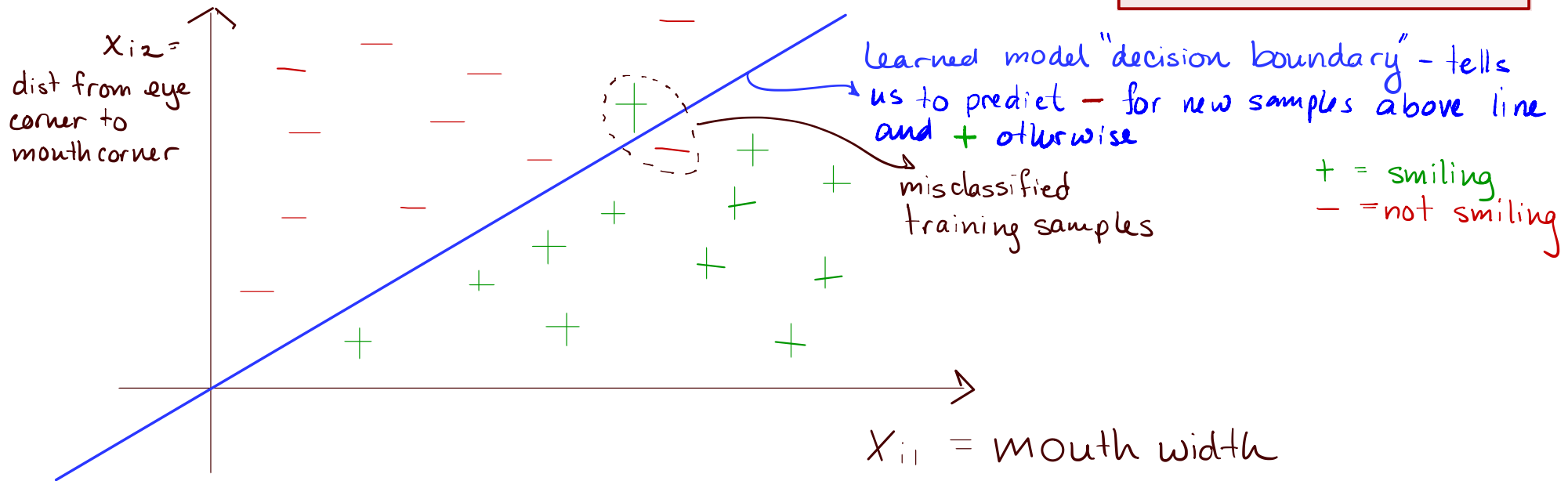
$\underline{x}_i = i^{\text{th}}$ sample's features

$x_{ij} = j^{\text{th}}$ feature of i^{th} sample

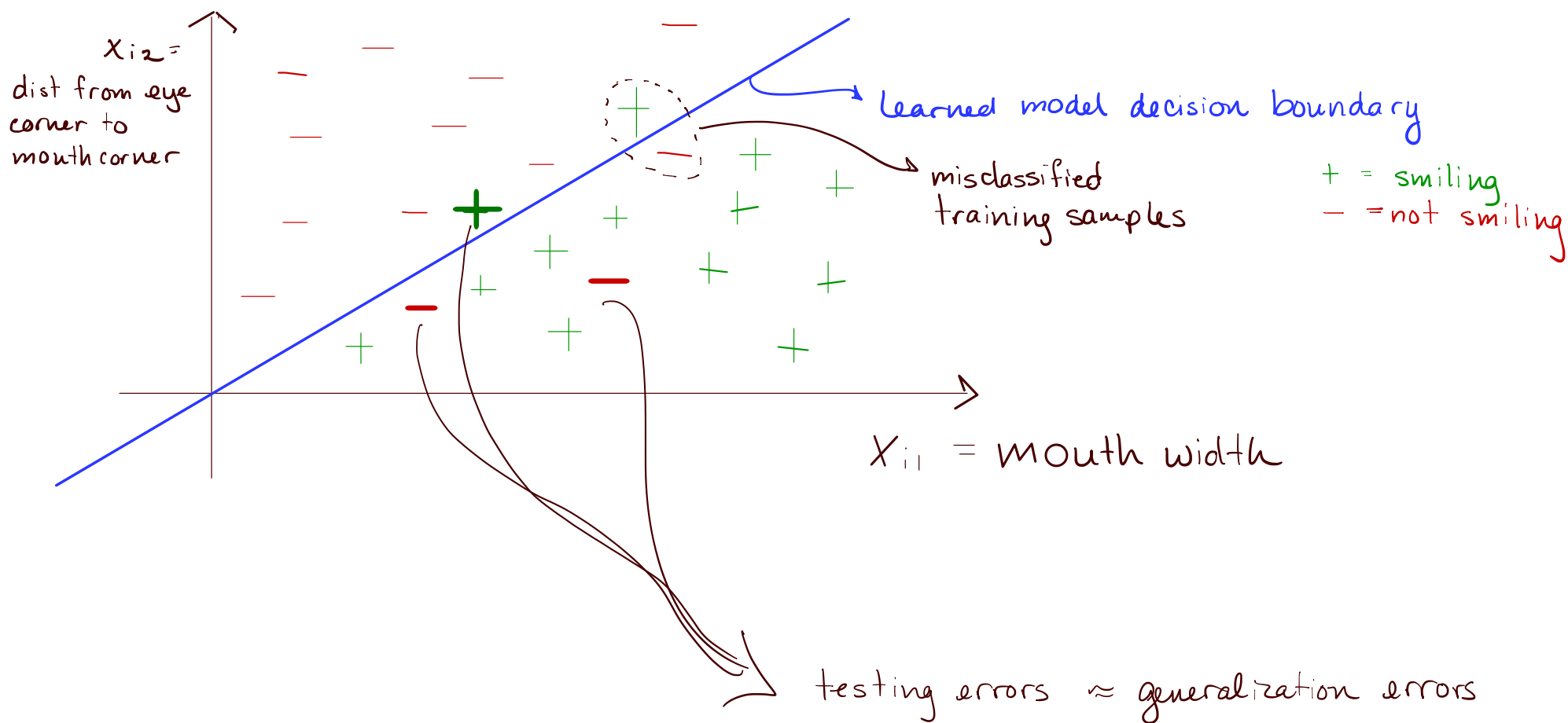
⑤ To learn model, we choose a loss function = a measure of how well a model fits data - e.g. % of samples misclassified as "smiling"

⑥ Finally, learn the model - search over collection of candidate models or model parameters to find one that minimizes loss on training data

some models learn new "features" from original input features



⑦ Characterize **generalization error** - error of our prediction on new data that was not used for training. Sometimes we estimate this using a set of test samples not used for training



OUR FIRST ML PROBLEM — CLASSIFICATION

Learning we observe training data (\underline{x}_i, y_i) for $i=1, \dots, n$
where $\underline{x}_i \in \mathbb{R}^p$ is a vector of p real numbers called the **feature**
and $y_i \in \mathbb{R}$ or $y_i \in \{-1, +1\}$ or $y_i \in \{0, 1\}$ is the **label**

Our **goal** learn a model that predicts a label \hat{y} given a feature vector \underline{x} .

Ex linear model $\hat{y} = w_1 x_{01} + w_2 x_{02} + \dots + w_p x_{0p}$

$w_1, \dots, w_p =$ weights to be learned from data

This is tedious to write!

Let's use some shorthand

that will make many things easier

let $\underline{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_p \end{bmatrix} \in \mathbb{R}^p$ be the weight vector
 \uparrow real numbers

let $\underline{x}_0 = \begin{bmatrix} x_{01} \\ x_{02} \\ \vdots \\ x_{0p} \end{bmatrix} \in \mathbb{R}^p$ be the feature vector

Then our linear model can be equivalently written as

$$\hat{y} = \langle \underline{w}, \underline{x}_0 \rangle = \underline{w}^T \underline{x}_0 = [w_1, \dots, w_p] \begin{bmatrix} x_{01} \\ x_{02} \\ \vdots \\ x_{0p} \end{bmatrix} = \underline{x}_0^T \underline{w} = \langle \underline{x}_0, \underline{w} \rangle$$

Inner product
of two vectors

vector
transpose

Ex $p=2$ $\underline{w} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$ When is $\hat{y} = \langle \underline{w}, \underline{x}_0 \rangle > 0$ and when is $\hat{y} < 0$?

$$\langle \underline{w}, \underline{x}_0 \rangle = w_1 x_{01} + w_2 x_{02} > 0$$

$$\Rightarrow -2x_{01} + x_{02} > 0$$

$$\Rightarrow x_{01} < x_{02}/2$$

Line = set of \underline{x}_0
where $\hat{y} = 0$

