1. Introduction

Example:

Use ML to learn a predictor for the maximum daytime temperature for a specific day's minimum temperature observed in the morning.

1. Download recordings of min : max daytime temperatures for the most recent days and denote the dataset by:

2. ML will learn a hypothesis Naz N(x) = y <- output prediction/ hypothesis/approximation

hypothesis map:

- reads in data points (low level properties)
 and delivers a prediction
- ML methods learn a vypomesis map from a typically large set of candidate maps to condidate maps are vypomesis space or model underlying on ML method

Based on visualization of (x"), yes) we can approximate Eynw, x + wo f with weights whelk!

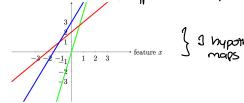
We will restrict the ML method to only consider linear mags has:= w1x+w0 w161Rt w061R

> monotonically increasing

Lethis is a hypothesis space L_{p} parameterized by $\ddot{w} = [w_{0}]$ indication: $N^{(\omega)}(x) = w_{1}x + \omega_{0}$

3. Choose between a space of hypothesis to try and find the best one.

loss functions: quentify the quality of $h^{(w)}(x)$ a hypothesis map.



· Stating from one initial guess, ML method will continually improve based on new observed data

1.2 Flavours in Machine Learning

- * Features: properties that we measure or compute easily in an automated Gashion.
- ·Labels. properties that connot be measured easily
- 1.1.1 Supervised Learning

·Using training sets will labeled data points for which we know the correct label values

1.1.2 Unsupervised Learning

·Using training sets will labelled data points for which we don't know the correct lides values

1.1.3 Unsupervised learning

·loss function to evaluate and compare different hypomeses

Lo assigns a non-neg loss val to a pair of dota paint and a hypomesis, but of large hypothesis space