

Learning From Data
Lecture 9
Logistic Regression and Gradient Descent

Logistic Regression
Gradient Descent

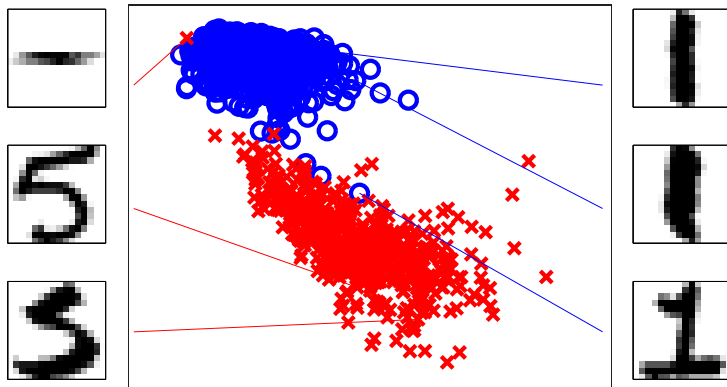
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CSCI 4100/6100

RECAP: Linear Classification and Regression

The linear signal:

$$s = \mathbf{w}^T \mathbf{x}$$

Good Features are Important



Before looking at the data, we can **reason** that symmetry and intensity should be good features based on our knowledge of the problem.

Algorithms

Linear Classification.

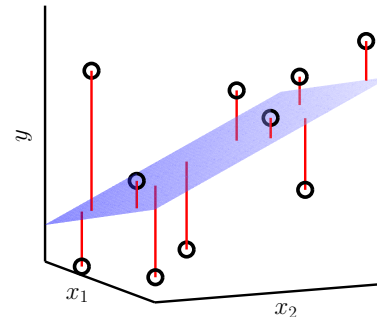
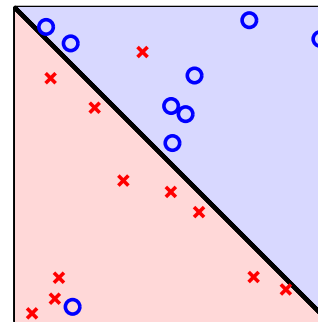
Pocket algorithm can tolerate errors
Simple and efficient

Linear Regression.

Single step learning:

$$\mathbf{w} = \mathbf{X}^\dagger \mathbf{y} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

Very efficient $O(Nd^2)$ *exact* algorithm.



Predicting a Probability

Will someone have a heart attack over the next year?

age	62 years
gender	male
blood sugar	120 mg/dL40,000
HDL	50
LDL	120
Mass	190 lbs
Height	5' 10''
...	...

Classification: Yes/No

Logistic Regression: Likelihood of heart attack

logistic regression $\equiv y \in [0, 1]$

$$h(\mathbf{x}) = \theta \left(\sum_{i=0}^d w_i x_i \right) = \theta(\mathbf{w}^T \mathbf{x})$$

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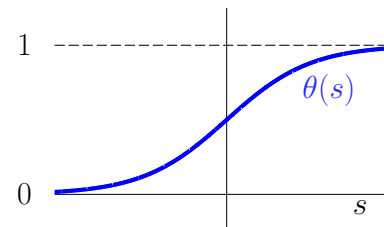
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$$h(\mathbf{x}) = \theta \left(\sum_{i=0}^d w_i x_i \right) = \theta(\mathbf{w}^T \mathbf{x})$$



$$\theta(s) = \frac{e^s}{1 + e^s} = \frac{1}{1 + e^{-s}}$$
$$\theta(-s) = \frac{e^{-s}}{1 + e^{-s}} = \frac{1}{1 + e^s} = 1 - \theta(s).$$

The Data is Still Binary, ± 1

$$\mathcal{D} = (\mathbf{x}_1, y_1 = \pm 1), \dots, (\mathbf{x}_N, y_N = \pm 1)$$

\mathbf{x}_n \leftarrow a person's health information

$y_n = \pm 1$ \leftarrow **did** they have a heart attack or not

We cannot measure a *probability*.

We can only see the occurrence of an event and try to *infer* a probability.

The Target Function is Inherently Noisy

$$f(\mathbf{x}) = \mathbb{P}[y = +1 \mid \mathbf{x}].$$

The data is generated from a *noisy* target function:

$$P(y \mid \mathbf{x}) = \begin{cases} f(\mathbf{x}) & \text{for } y = +1; \\ 1 - f(\mathbf{x}) & \text{for } y = -1. \end{cases}$$

What Makes an h Good?

‘fitting’ the data means finding a good h

$$h \text{ is good if: } \begin{cases} h(\mathbf{x}_n) \approx 1 & \text{whenever } y_n = +1; \\ h(\mathbf{x}_n) \approx 0 & \text{whenever } y_n = -1. \end{cases}$$

A simple error measure that captures this:

$$E_{\text{in}}(h) = \frac{1}{N} \sum_{n=1}^N \left(h(\mathbf{x}_n) - \frac{1}{2}(1 + y_n) \right)^2.$$

Not very convenient (hard to minimize).

The Cross Entropy Error Measure

$$E_{\text{in}}(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \cdot \mathbf{w}^T \mathbf{x}_n})$$

It looks complicated and ugly (\ln , $e^{(\cdot)}$, \dots),

But,

- it is based on an intuitive probabilistic interpretation of h .
- it is very convenient and mathematically friendly (‘easy’ to minimize).

Verify: $y_n = +1$ encourages $\mathbf{w}^T \mathbf{x}_n \gg 0$, so $\theta(\mathbf{w}^T \mathbf{x}_n) \approx 1$; $y_n = -1$ encourages $\mathbf{w}^T \mathbf{x}_n \ll 0$, so $\theta(\mathbf{w}^T \mathbf{x}_n) \approx 0$;

The Probabilistic Interpretation

Suppose that $h(\mathbf{x}) = \theta(\mathbf{w}^T \mathbf{x})$ closely captures $\mathbb{P}[+1|\mathbf{x}]$:

$$P(y | \mathbf{x}) = \begin{cases} \theta(\mathbf{w}^T \mathbf{x}) & \text{for } y = +1; \\ 1 - \theta(\mathbf{w}^T \mathbf{x}) & \text{for } y = -1. \end{cases}$$

The Probabilistic Interpretation

So, if $h(\mathbf{x}) = \theta(\mathbf{w}^T \mathbf{x})$ closely captures $\mathbb{P}[+1|\mathbf{x}]$:

$$P(y | \mathbf{x}) = \begin{cases} \theta(\mathbf{w}^T \mathbf{x}) & \text{for } y = +1; \\ \theta(-\mathbf{w}^T \mathbf{x}) & \text{for } y = -1. \end{cases}$$

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... or, more compactly,

$$P(y | \mathbf{x}) = \theta(y \cdot \mathbf{w}^T \mathbf{x})$$

The Likelihood

$$P(y \mid \mathbf{x}) = \theta(y \cdot \mathbf{w}^T \mathbf{x})$$

Recall: $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)$ are independently generated

Likelihood:

The probability of getting the y_1, \dots, y_N in \mathcal{D} from the corresponding $\mathbf{x}_1, \dots, \mathbf{x}_N$:

$$P(y_1, \dots, y_N \mid \mathbf{x}_1, \dots, \mathbf{x}_n) = \prod_{n=1}^N P(y_n \mid \mathbf{x}_n).$$

The likelihood measures the probability that the data were generated if f were h .

Maximizing The Likelihood (why?)

$$\begin{aligned} & \max \quad \prod_{n=1}^N P(y_n | \mathbf{x}_n) \\ \Leftrightarrow & \max \quad \ln \left(\prod_{n=1}^N P(y_n | \mathbf{x}_n) \right) \\ \equiv & \max \quad \sum_{n=1}^N \ln P(y_n | \mathbf{x}_n) \\ \Leftrightarrow & \min \quad - \frac{1}{N} \sum_{n=1}^N \ln P(y_n | \mathbf{x}_n) \\ \equiv & \min \quad \frac{1}{N} \sum_{n=1}^N \ln \frac{1}{P(y_n | \mathbf{x}_n)} \\ \equiv & \min \quad \frac{1}{N} \sum_{n=1}^N \ln \frac{1}{\theta(y_n \cdot \mathbf{w}^T \mathbf{x}_n)} \\ \equiv & \min \quad \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \cdot \mathbf{w}^T \mathbf{x}_n}) \end{aligned}$$

← we specialize to our “model” here

$$E_{\text{in}}(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \cdot \mathbf{w}^T \mathbf{x}_n})$$

How To Minimize $E_{\text{in}}(\mathbf{w})$

Classification – PLA/Pocket (iterative)

Regression – pseudoinverse (analytic), from solving $\nabla_{\mathbf{w}} E_{\text{in}}(\mathbf{w}) = \mathbf{0}$.

Logistic Regression – analytic won't work.

Numerically/iteratively set $\nabla_{\mathbf{w}} E_{\text{in}}(\mathbf{w}) \rightarrow \mathbf{0}$.

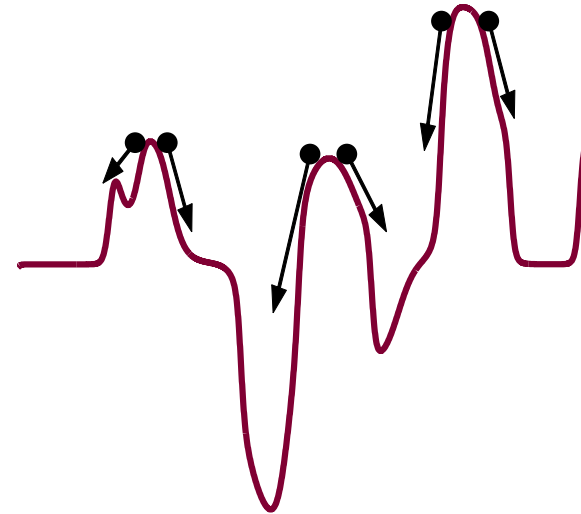
Finding The Best Weights - Hill Descent

Ball on a complicated hilly terrain

— rolls down to a *local valley*



this is called a *local minimum*

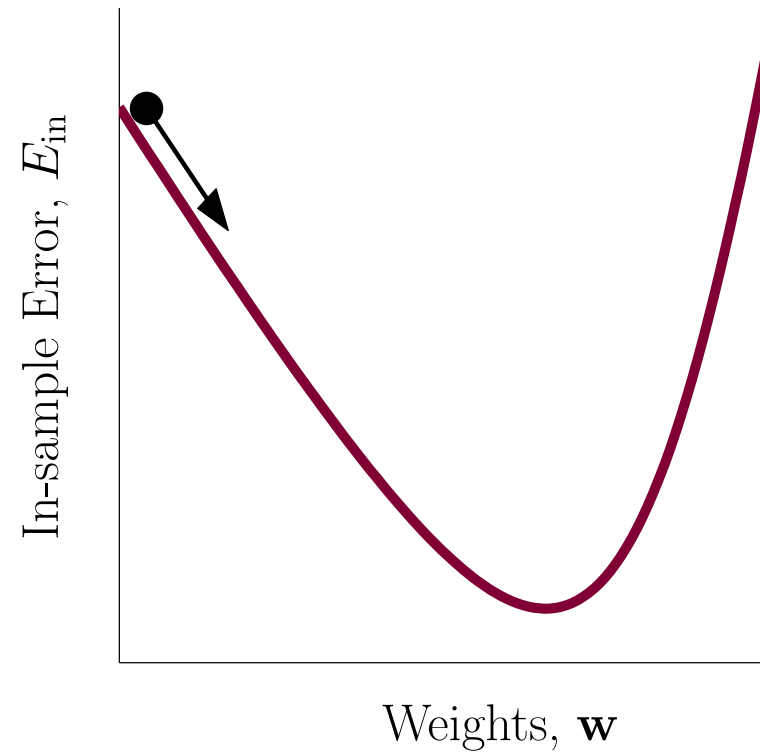


Questions:

How to get to the bottom of the deepest valey?

How to do this when we don't have gravity?

Our E_{in} Has Only One Valley



... because $E_{\text{in}}(\mathbf{w})$ is a **convex function** of w .

(So, who care's if it looks ugly!)

How to “Roll Down”?

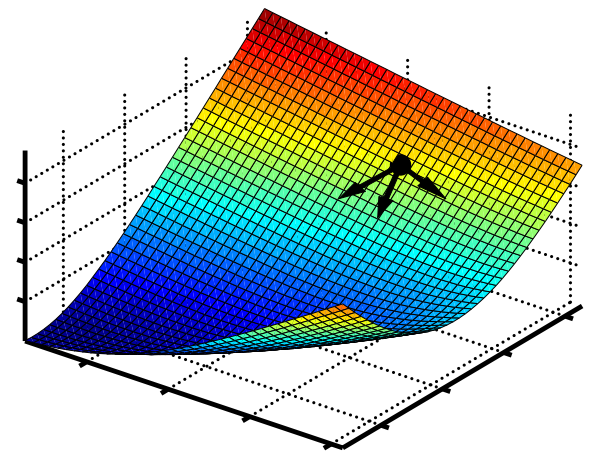
Assume you are at weights $\mathbf{w}(t)$ and you take a step of size η in the direction $\hat{\mathbf{v}}$.

$$\mathbf{w}(t + 1) = \mathbf{w}(t) + \eta \hat{\mathbf{v}}$$

We get to pick $\hat{\mathbf{v}}$

← what’s the best direction to take the step?

Pick $\hat{\mathbf{v}}$ to make $E_{\text{in}}(\mathbf{w}(t + 1))$ as small as possible.



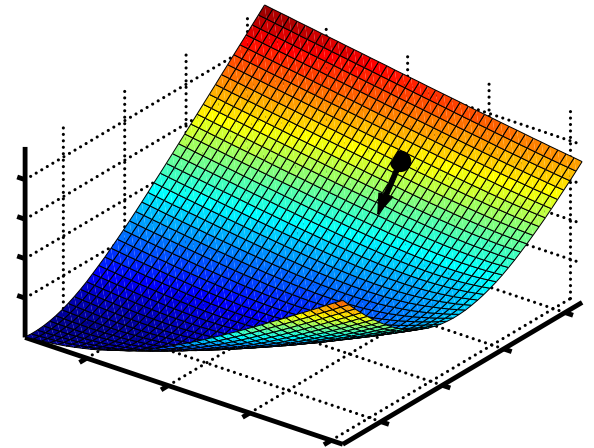
The Gradient is the Fastest Way to Roll Down

Approximating the change in E_{in}

$$\begin{aligned}\Delta E_{\text{in}} &= E_{\text{in}}(\mathbf{w}(t+1)) - E_{\text{in}}(\mathbf{w}(t)) \\ &= E_{\text{in}}(\mathbf{w}(t) + \eta \hat{\mathbf{v}}) - E_{\text{in}}(\mathbf{w}(t)) \\ &= \eta \underbrace{\nabla E_{\text{in}}(\mathbf{w}(t))^\top \hat{\mathbf{v}}}_{\text{minimized at } \hat{\mathbf{v}} = -\frac{\nabla E_{\text{in}}(\mathbf{w}(t))}{\|\nabla E_{\text{in}}(\mathbf{w}(t))\|}} + O(\eta^2) \quad (\text{Taylor's Approximation})\end{aligned}$$

$$\text{minimized at } \hat{\mathbf{v}} = -\frac{\nabla E_{\text{in}}(\mathbf{w}(t))}{\|\nabla E_{\text{in}}(\mathbf{w}(t))\|}$$

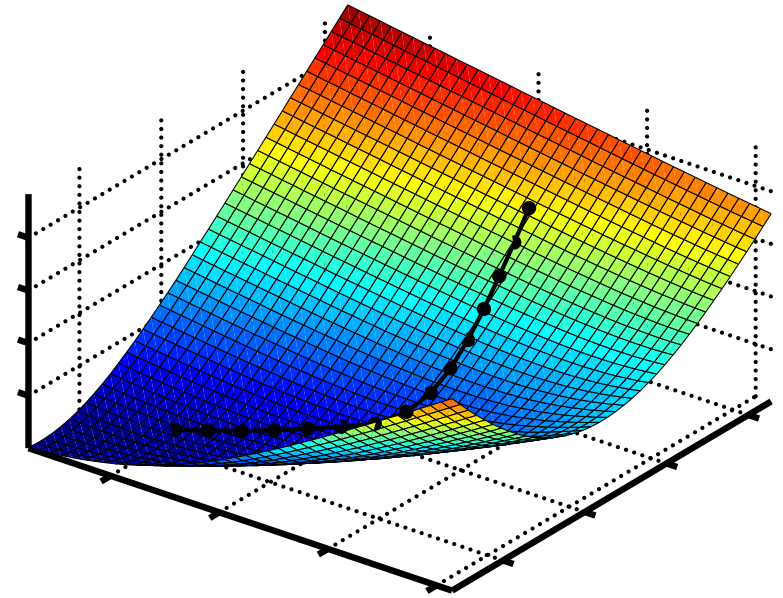
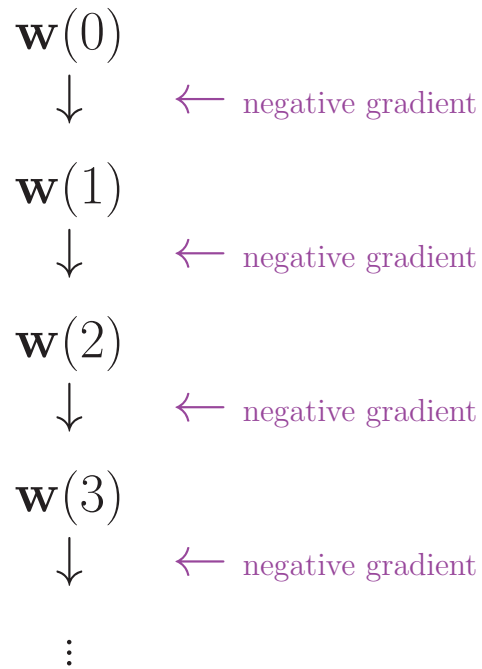
$$\approx -\eta \|\nabla E_{\text{in}}(\mathbf{w}(t))\| \quad \leftarrow \text{attained at } \hat{\mathbf{v}} = -\frac{\nabla E_{\text{in}}(\mathbf{w}(t))}{\|\nabla E_{\text{in}}(\mathbf{w}(t))\|}$$



The best (steepest) direction to move is the negative gradient:

$$\hat{\mathbf{v}} = -\frac{\nabla E_{\text{in}}(\mathbf{w}(t))}{\|\nabla E_{\text{in}}(\mathbf{w}(t))\|}$$

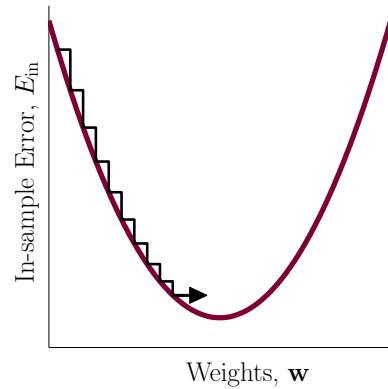
“Rolling Down” \equiv Iterating the Negative Gradient



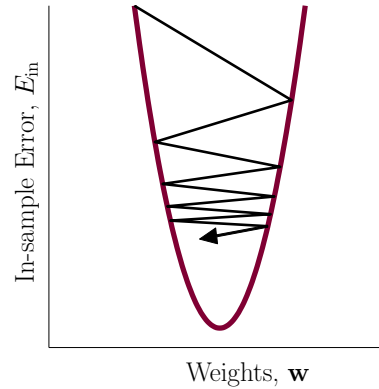
$\eta = 0.5$; 15 steps

The 'Goldilocks' Step Size

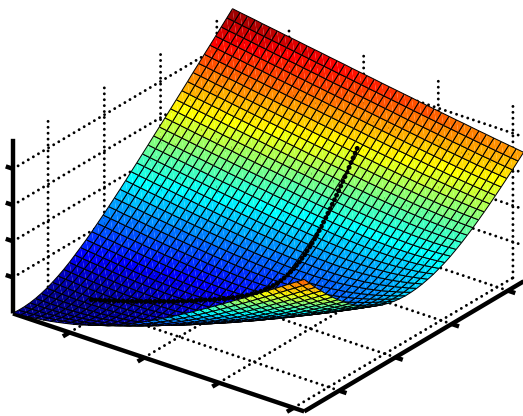
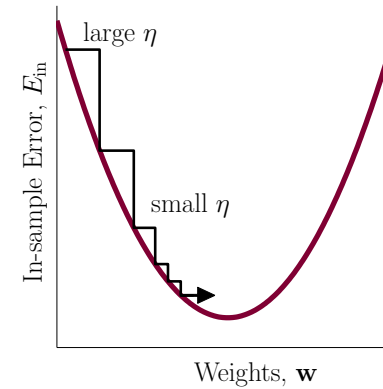
η too small



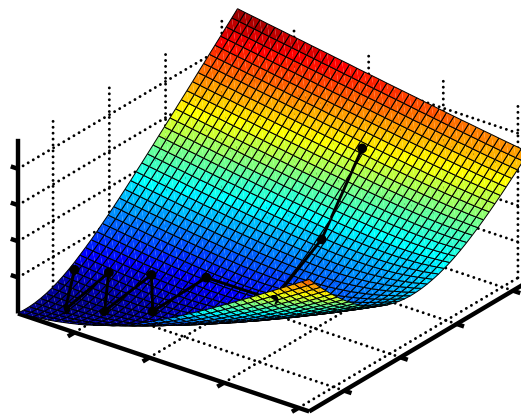
η too large



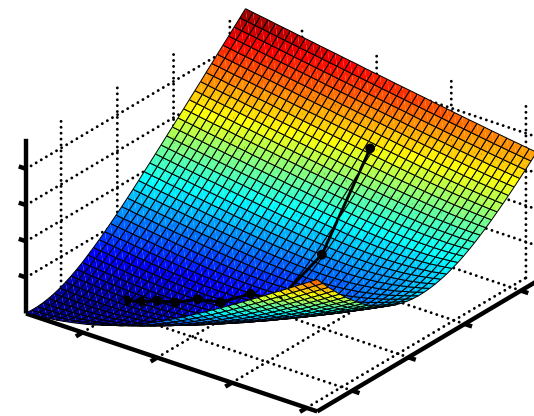
variable η_t – just right



$\eta = 0.1$; 75 steps



$\eta = 2$; 10 steps



variable η_t ; 10 steps

Fixed Learning Rate Gradient Descent

$$\eta_t = \eta \cdot \|\nabla E_{\text{in}}(\mathbf{w}(t))\|$$

$\|\nabla E_{\text{in}}(\mathbf{w}(t))\| \rightarrow 0$ when closer to the minimum.

$$\begin{aligned}\eta_t \hat{\mathbf{v}} &= -\eta_t \cdot \frac{\nabla E_{\text{in}}(\mathbf{w}(t))}{\|\nabla E_{\text{in}}(\mathbf{w}(t))\|} \\ &= -\eta \cdot \frac{\nabla E_{\text{in}}(\mathbf{w}(t))}{\|\nabla E_{\text{in}}(\mathbf{w}(t))\|} \cdot \frac{\|\nabla E_{\text{in}}(\mathbf{w}(t))\|}{\|\nabla E_{\text{in}}(\mathbf{w}(t))\|}\end{aligned}$$

$$\eta_t \hat{\mathbf{v}} = -\eta \cdot \nabla E_{\text{in}}(\mathbf{w}(t))$$

1: Initialize at step $t = 0$ to $\mathbf{w}(0)$.

2: **for** $t = 0, 1, 2, \dots$ **do**

3: Compute the gradient

$$\mathbf{g}_t = \nabla E_{\text{in}}(\mathbf{w}(t)).$$

← (Ex. 3.7 in LFD)

4: Move in the direction $\mathbf{v}_t = -\mathbf{g}_t$.

5: Update the weights:

$$\mathbf{w}(t+1) = \mathbf{w}(t) + \eta \mathbf{v}_t.$$

6: Iterate ‘until it is time to stop’.

7: **end for**

8: Return the final weights.

Gradient descent can minimize any smooth function, for example

$$E_{\text{in}}(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \cdot \mathbf{w}^T \mathbf{x}})$$

← logistic regression

Stochastic Gradient Descent (SGD)

A variation of GD that considers only the error on one data point.

$$E_{\text{in}}(\mathbf{w}) = \frac{1}{N} \sum_{n=1}^N \ln(1 + e^{-y_n \cdot \mathbf{w}^T \mathbf{x}_n}) = \frac{1}{N} \sum_{n=1}^N e(\mathbf{w}, \mathbf{x}_n, y_n)$$

- Pick a random data point (\mathbf{x}_*, y_*)
- Run an iteration of GD on $e(\mathbf{w}, \mathbf{x}_*, y_*)$

$$\mathbf{w}(t+1) \leftarrow \mathbf{w}(t) - \eta \nabla_{\mathbf{w}} e(\mathbf{w}, \mathbf{x}_*, y_*)$$

1. The ‘average’ move is the same as GD;
2. Computation: fraction $\frac{1}{N}$ cheaper per step;
3. Stochastic: helps escape local minima;
4. Simple;
5. Similar to PLA.

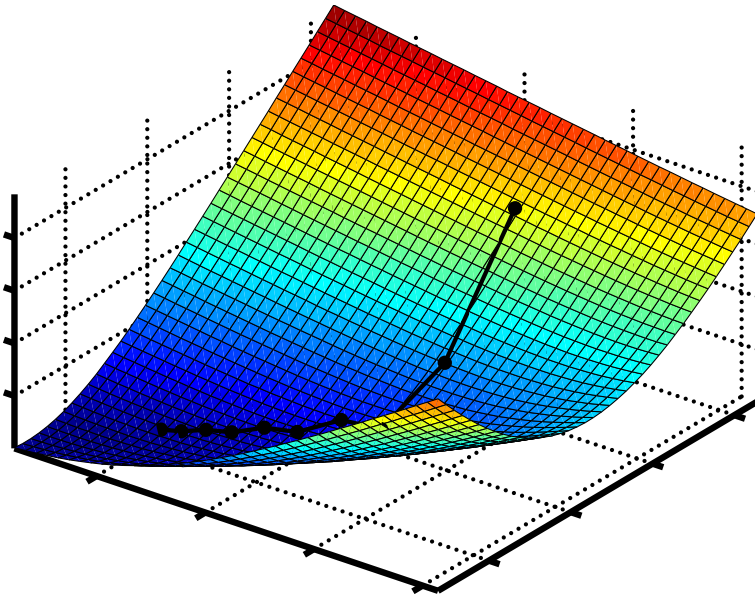
Logistic Regression:

$$\mathbf{w}(t+1) \leftarrow \mathbf{w}(t) + y_* \mathbf{x}_* \left(\frac{\eta}{1 + e^{y_* \mathbf{w}^T \mathbf{x}_*}} \right)$$

(Recall PLA: $\mathbf{w}(t+1) \leftarrow \mathbf{w}(t) + y_* \mathbf{x}_*$)

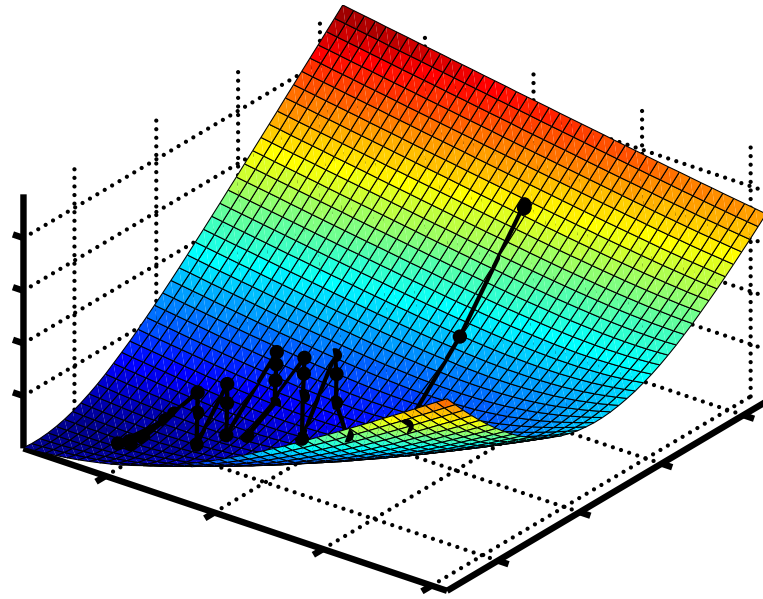
Stochastic Gradient Descent

GD



$\eta = 6$
10 steps
 $N = 10$

SGD



$\eta = 2$
30 steps

