# Neural Network Optimization

# Machine Learning Problems

$w$: parameter

- **Given data:**

$$\{(x_i, y_i)\}_{i=1}^n \qquad x_i \in \mathbb{R}^d \qquad y_i \in \mathbb{R}$$

- **Learning a model's parameters:** $\min_w \sum_{i=1}^n \ell_i(w)$

$$\text{Logistic Loss: } \ell_i(w) = \log(1 + \exp(-y_i\, x_i^T w))$$

$$\text{Squared error Loss: } \ell_i(w) = (y_i - x_i^T w)^2$$

# Machine Learning Problems

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- **Learning a model's parameters:** $\sum_{i=1}^n \ell_i(w)$

Logistic Loss: $\ell_i(w) = \log(1 + \exp(-y_i\, x_i^T w))$

Squared error Loss: $\ell_i(w) = (y_i - x_i^T w)^2$

$t = 1, \ldots, T$ iteration

Gradient Descent:

$$w_{t+1} = w_t - \underline{\eta} \nabla_w \left( \frac{1}{n} \sum_{i=1}^n \ell_i(w) \right) \Big|_{w=w_t}$$

$\eta$: step size, learning rate

start from $\underline{w_0}$: 0-init

Kaiming Init

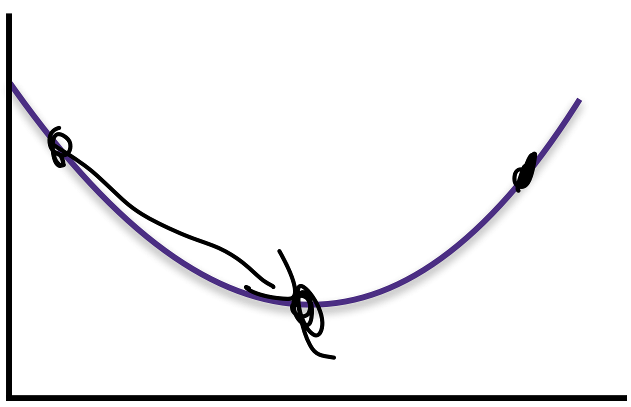
# Gradient Descent

$$\text{Initialize: } w_0 = 0$$

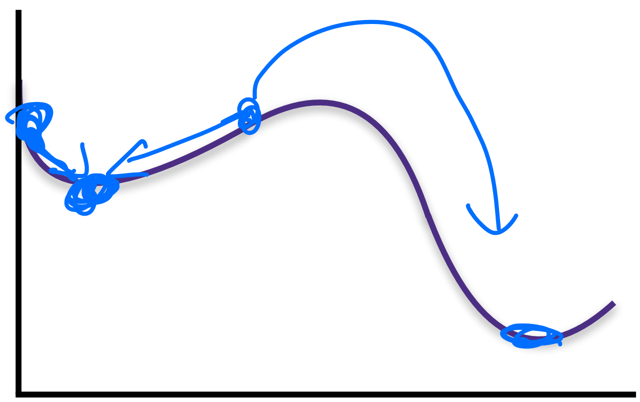
$$\text{for } t = 1, 2, \ldots$$

$$w_{t+1} = w_t - \eta \nabla f(w_t)$$

**Convex Function**

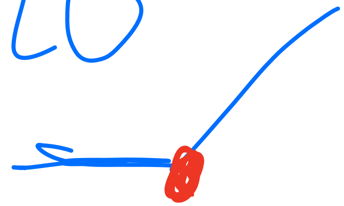


**Non-convex Function**



# Sub-Gradient Descent

ReLU



for ReLU: $[0,1]$

Initialize: $w_0 = 0$

for $t = 1, 2, \ldots$

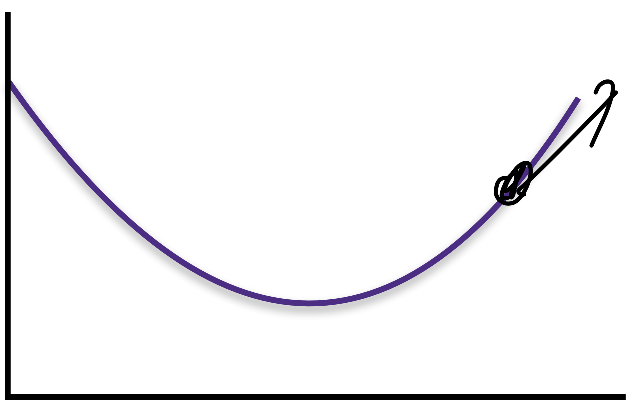
Find any $g_t$ such that $f(y) \geq f(w_t) + g_t^\top (y - w_t)$

$w_{t+1} = w_t - \eta g_t$

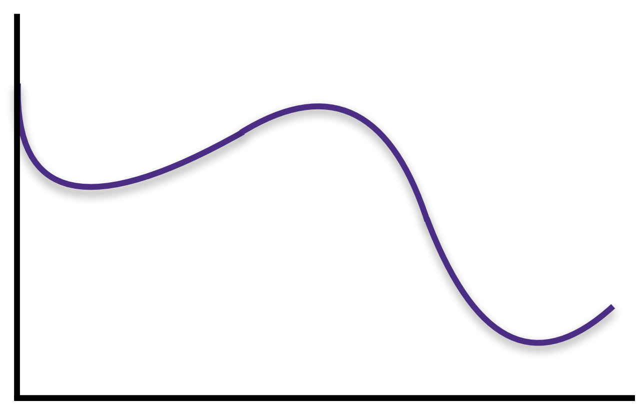
$g$ is a subgradient at $x$ if $f(y) \geq f(x) + g^T(y - x)$

$- g^T(x-y)$

**Convex Function**



**Non-convex Function**



# Machine Learning Problems

- **Given data:**

$$\{(x_i, y_i)\}_{i=1}^n \qquad x_i \in \mathbb{R}^d \qquad y_i \in \mathbb{R}$$

- **Learning a model's parameters:** $\displaystyle\sum_{i=1}^n \ell_i(w)$

$O(n)$

Gradient Descent:

$$w_{t+1} = w_t - \eta \nabla_w \left( \frac{1}{n} \sum_{i=1}^n \ell_i(w) \right) \Big|_{w=w_t}$$

Stochastic Gradient Descent:

$$w_{t+1} = w_t - \eta \nabla_w \ell_{I_t}(w) \Big|_{w=w_t}$$

$I_t$ drawn uniform at random from $\{1, \ldots, n\}$

$\mathbb{E}[\quad] =$

# Mini-batch SGD

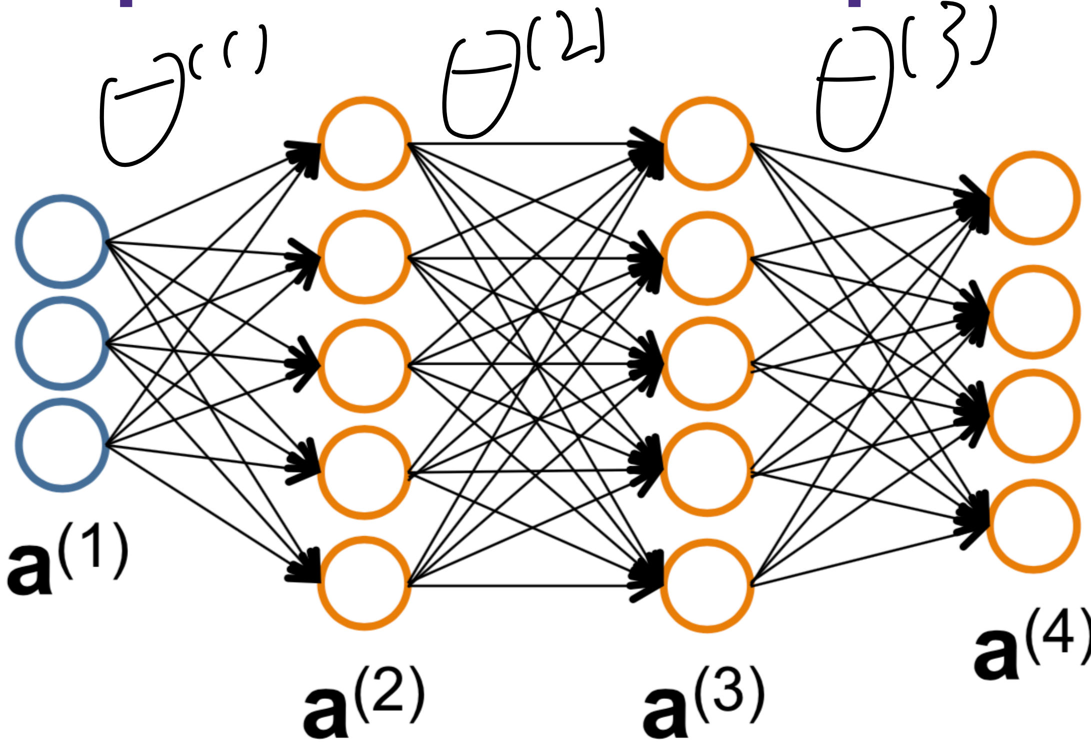
Instead of one iterate, average B stochastic gradient together

Advantages:

- de-noises gradient
- Matrix computations
- Parallelization

# Gradient Computation on a Graph

$L$: # of layers




Naive computation: node by node

$$\frac{\partial L}{\partial \Theta^{(1)}} : O(L) \Rightarrow \text{in total } O(L^2)$$

# A brief history

- **Back propagation:** the workhorse for training neural networks. An algorithm that for a network with V nodes and E edges calculates that gradient in **linear time** O(V+E).

- The name was introduced by Rumelhart, Hinton, Williams '86. Same idea was rediscovered multiple times. Also mentioned in Werbos' thesis '74 in the context of neural networks.

- **Control theory:** Kelly '60, Bryson '61 [**dynamic programming**]

- **Theoretical computer science:** Baur-Strassen lemma '83 [**algebraic circuits**]

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

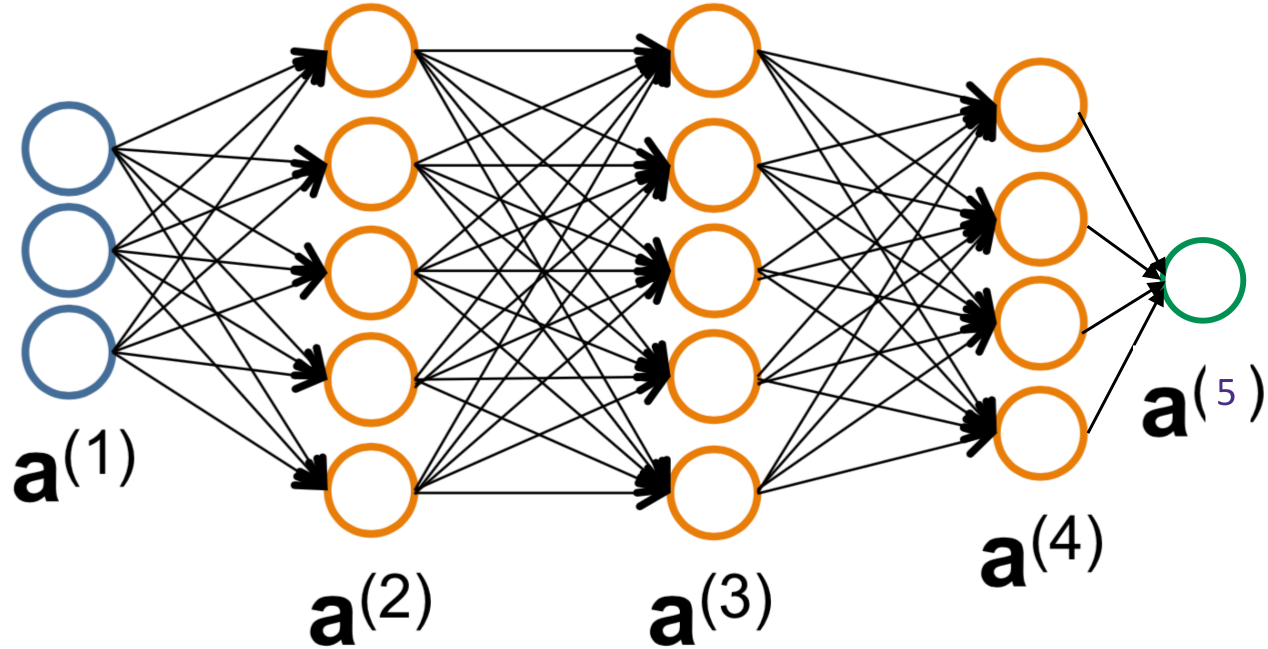
$$\vdots$$

$$z^{(l+1)} = \Theta^{(l)} a^{(l)}$$

$$a^{(l+1)} = g\left(z^{(l+1)}\right)$$

$$\vdots$$

$$\widehat{y} = g(\Theta^{(L)} a^{(L)})$$




$$L(y, \widehat{y}) = y \log(\widehat{y}) + (1 - y)\log(1 - \widehat{y})$$

$$g(z) = \frac{1}{1 + e^{-z}}$$

Gradient Descent: $\Theta^{(l)} \leftarrow \Theta^{(l)} - \eta \nabla_{\Theta^{(l)}} L(y, \widehat{y}) \qquad \forall l$

# Forward Propagation

$L$: # of layer
(ignore bias)
$g$: activation function
$z^{(l)}$: pre-activation

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

$$\vdots$$

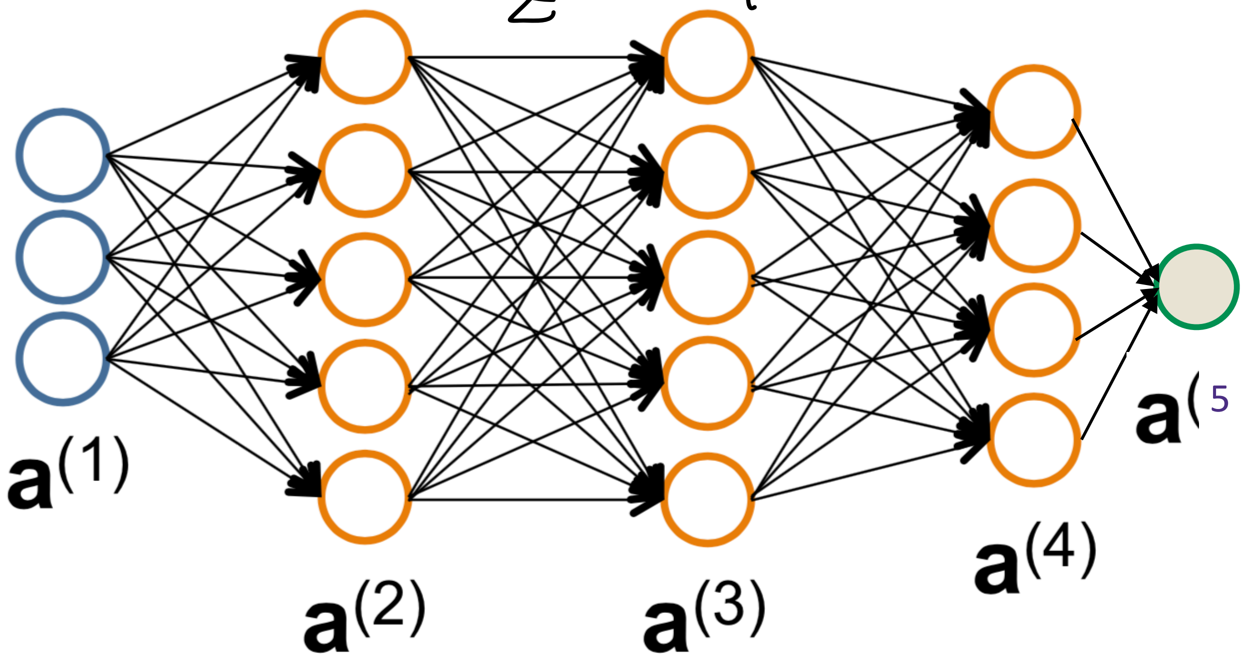
$$a^{(l)} = g(z^{(l)})$$

$$z^{(l+1)} = \Theta^{(l)} a^{(l)}$$

$$a^{(l+1)} = g\left(z^{(l+1)}\right)$$

$$\vdots$$

$$\hat{y} = a^{(L+1)}$$




$$L(y, \hat{y}) = y \log(\hat{y}) + (1 - y)\log(1 - \hat{y})$$

$$g(z) = \frac{1}{1 + e^{-z}}$$

# Backprop

$X \in \mathbb{R}^d$, $\Theta^{(1)}, \ldots, \Theta^{(L)}$ : parameters to train

$\Theta^{(1)} : \mathbb{R}^{m \times d}$, $\Theta^{(2)}, \ldots, \Theta^{(L-1)} : \mathbb{R}^{m \times m}$, $\Theta^{(L)} : \mathbb{R}^{m}$

$m$ : width

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

$$\vdots$$

$$a^{(l)} = g(z^{(l)})$$

$$z^{(l+1)} = \Theta^{(l)} a^{(l)}$$

$$a^{(l+1)} = g\left(z^{(l+1)}\right)$$

$$\vdots$$

$$\hat{y} = a^{(L+1)}$$

**Train by Stochastic Gradient Descent:**

$\Theta^{(l)}_{i,j} \in \mathbb{R}$

$$\Theta^{(l)}_{i,j} \leftarrow \Theta^{(l)}_{i,j} - \eta \frac{\partial L(y, \hat{y})}{\partial \Theta^{(l)}_{i,j}}$$

$$L(y, \hat{y}) = y \log(\hat{y}) + (1 - y)\log(1 - \hat{y})$$

$$g(z) = \frac{1}{1 + e^{-z}} \qquad \delta_i^{(l+1)} = \frac{\partial L(y, \hat{y})}{\partial z_i^{(l+1)}}$$

# Backprop

Chain Rule $z_i^{(l+1)} = \sum_{j=1}^{m} \Theta_{i,j}^{(l)} \cdot a_j^{(l)}$

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

$$\vdots$$

$$a^{(l)} = g(z^{(l)})$$

$$z^{(l+1)} = \Theta^{(l)} a^{(l)}$$

$$a^{(l+1)} = g\left(z^{(l+1)}\right)$$

$$\vdots$$

$$\hat{y} = a^{(L+1)}$$

$$\frac{\partial L(y, \hat{y})}{\partial \Theta_{i,j}^{(l)}} = \frac{\partial L(y, \hat{y})}{\partial z_i^{(l+1)}} \cdot \frac{\partial z_i^{(l+1)}}{\partial \Theta_{i,j}^{(l)}} =: \boxed{\delta_i^{(l+1)}} \cdot a_j^{(l)}$$

**Train by Stochastic Gradient Descent:**

$$\Theta_{i,j}^{(l)} \leftarrow \Theta_{i,j}^{(l)} - \eta \frac{\partial L(y, \hat{y})}{\partial \Theta_{i,j}^{(l)}}$$

$$L(y, \hat{y}) = y \log(\hat{y}) + (1 - y)\log(1 - \hat{y})$$

$$g(z) = \frac{1}{1 + e^{-z}} \qquad \delta_i^{(l+1)} = \frac{\partial L(y, \hat{y})}{\partial z_i^{(l+1)}}$$

# Backprop

Key idea: relate $\delta^{(l)}$ to $\delta^{(l+1)}$

$$\frac{\partial L(y,\hat{y})}{\partial \Theta_{i,j}^{(l)}} = \frac{\partial L(y,\hat{y})}{\partial z_i^{(l+1)}} \cdot \frac{\partial z_i^{(l+1)}}{\partial \Theta_{i,j}^{(l)}} =: \delta_i^{(l+1)} \cdot a_j^{(l)}$$

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

$$\vdots$$

$$a^{(l)} = g(z^{(l)})$$

$$z^{(l+1)} = \Theta^{(l)} a^{(l)}$$

$$a^{(l+1)} = g\left(z^{(l+1)}\right)$$

$$\vdots$$

$$\hat{y} = a^{(L+1)}$$

$$\delta_i^{(l)} = \frac{\partial L(y,\hat{y})}{\partial z_i^{(l)}} = \sum_k \underbrace{\frac{\partial L(y,\hat{y})}{\partial z_k^{(l+1)}}}_{\delta_k^{(l+1)}} \cdot \underbrace{\frac{\partial z_k^{(l+1)}}{\partial z_i^{(l)}}}_{\Theta_{k,i}^{(l)} \cdot g'(z_i^{(l)})}$$

$$\rightarrow z_k^{(l+1)} = \sum_{u=1}^{m} \Theta_{k,u}^{(l)} \cdot g(z_u^{(l)})$$

$$L(y,\hat{y}) = y\log(\hat{y}) + (1-y)\log(1-\hat{y})$$

$$g(z) = \frac{1}{1+e^{-z}} \qquad \delta_i^{(l+1)} = \frac{\partial L(y,\hat{y})}{\partial z_i^{(l+1)}}$$

# Backprop

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

$$\vdots$$

$$a^{(l)} = g(z^{(l)})$$

$$z^{(l+1)} = \Theta^{(l)} a^{(l)}$$

$$a^{(l+1)} = g\left(z^{(l+1)}\right)$$

$$\vdots$$

$$\hat{y} = a^{(L+1)}$$

$$\boxed{\frac{\partial L(y,\hat{y})}{\partial \Theta^{(l)}_{i,j}} = \frac{\partial L(y,\hat{y})}{\partial z_i^{(l+1)}} \cdot \frac{\partial z_i^{(l+1)}}{\partial \Theta^{(l)}_{i,j}} =: \delta_i^{(l+1)} \cdot a_j^{(l)}}$$

$$\delta_i^{(l)} = \frac{\partial L(y,\hat{y})}{\partial z_i^{(l)}} = \sum_k \frac{\partial L(y,\hat{y})}{\partial z_k^{(l+1)}} \cdot \frac{\partial z_k^{(l+1)}}{\partial z_i^{(l)}}$$

$$= \sum_k \delta_k^{(l+1)} \cdot \Theta^{(l)}_{k,i}\, g'(z_i^{(l)})$$

if g: logistic

$$= a_i^{(l)}(1 - a_i^{(l)}) \sum_k \delta_k^{(l+1)} \cdot \Theta^{(l)}_{k,i}$$

$$L(y,\hat{y}) = y\log(\hat{y}) + (1-y)\log(1-\hat{y})$$

$$g(z) = \frac{1}{1+e^{-z}} \qquad \delta_i^{(l+1)} = \frac{\partial L(y,\hat{y})}{\partial z_i^{(l+1)}}$$

# Backprop

Recursion / Dynamic Programming

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

$$\vdots$$

$$a^{(l)} = g(z^{(l)})$$

$$z^{(l+1)} = \Theta^{(l)} a^{(l)}$$

$$a^{(l+1)} = g\left(z^{(l+1)}\right)$$

$$\vdots$$

$$\widehat{y} = a^{(L+1)}$$

$$\frac{\partial L(y, \widehat{y})}{\partial \Theta_{i,j}^{(l)}} = \frac{\partial L(y, \widehat{y})}{\partial z_i^{(l+1)}} \cdot \frac{\partial z_i^{(l+1)}}{\partial \Theta_{i,j}^{(l)}} =: \delta_i^{(l+1)} \cdot a_j^{(l)}$$

$$\delta_i^{(l)} = a_i^{(l)}(1 - a_i^{(l)}) \sum_k \delta_k^{(l+1)} \cdot \Theta_{k,i}^{(l)}$$

$$\delta^{(l+1)} \to \delta^{(l)} \to \delta^{(l-1)} \cdots \to \delta^{(1)}$$

$$\Theta^{(l)} \qquad \Theta^{(l-1)}$$

$$L(y, \widehat{y}) = y \log(\widehat{y}) + (1 - y)\log(1 - \widehat{y})$$

$$g(z) = \frac{1}{1 + e^{-z}} \qquad \delta_i^{(l+1)} = \frac{\partial L(y, \widehat{y})}{\partial z_i^{(l+1)}}$$

# Backprop

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

$$\vdots$$

$$a^{(l)} = g(z^{(l)})$$

$$z^{(l+1)} = \Theta^{(l)} a^{(l)}$$

$$a^{(l+1)} = g\left(z^{(l+1)}\right)$$

$$\vdots$$

$$\hat{y} = a^{(L+1)}$$

$$\frac{\partial L(y, \hat{y})}{\partial \Theta^{(l)}_{i,j}} = \frac{\partial L(y, \hat{y})}{\partial z_i^{(l+1)}} \cdot \frac{\partial z_i^{(l+1)}}{\partial \Theta^{(l)}_{i,j}} =: \delta_i^{(l+1)} \cdot a_j^{(l)}$$

$$\delta_i^{(l)} = a_i^{(l)}(1 - a_i^{(l)}) \sum_k \delta_k^{(l+1)} \cdot \Theta^{(l)}_{k,i}$$

$$\delta_i^{(L+1)} = \frac{\partial L(y, \hat{y})}{\partial z_i^{(L+1)}} = \frac{\partial}{\partial z_i^{(L+1)}} \left[ y \log(g(z^{(L+1)})) + (1-y)\log(1 - g(z^{(L+1)})) \right]$$

$$= \frac{y}{g(z^{(L+1)})} g'(z^{(L+1)}) - \frac{1-y}{1 - g(z^{(L+1)})} g'(z^{(L+1)})$$

$$= y - g(z^{(L+1)}) = y - a^{(L+1)}$$

$$L(y, \hat{y}) = y \log(\hat{y}) + (1-y)\log(1 - \hat{y})$$

$$g(z) = \frac{1}{1 + e^{-z}} \qquad \delta_i^{(l+1)} = \frac{\partial L(y, \hat{y})}{\partial z_i^{(l+1)}}$$

# Backprop

$$a^{(1)} = x$$

$$z^{(2)} = \Theta^{(1)} a^{(1)}$$

$$a^{(2)} = g\left(z^{(2)}\right)$$

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$$a^{(l)} = g(z^{(l)})$$

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$$\widehat{y} = a^{(L+1)}$$

$$\frac{\partial L(y, \widehat{y})}{\partial \Theta_{i,j}^{(l)}} = \frac{\partial L(y, \widehat{y})}{\partial z_i^{(l+1)}} \cdot \frac{\partial z_i^{(l+1)}}{\partial \Theta_{i,j}^{(l)}} =: \delta_i^{(l+1)} \cdot a_j^{(l)}$$

$$\delta_i^{(l)} = a_i^{(l)}(1 - a_i^{(l)}) \sum_k \delta_k^{(l+1)} \cdot \Theta_{k,i}^{(l)}$$

$$\delta^{(L+1)} = y - a^{(L+1)}$$

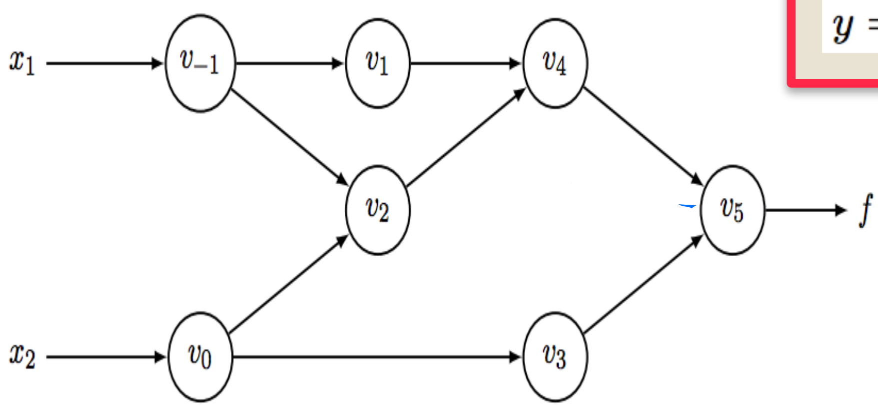
Recursive Algorithm!

$$L(y, \widehat{y}) = y \log(\widehat{y}) + (1 - y)\log(1 - \widehat{y})$$

$$g(z) = \frac{1}{1 + e^{-z}} \qquad \delta_i^{(l+1)} = \frac{\partial L(y, \widehat{y})}{\partial z_i^{(l+1)}}$$

# Auto-differentiation

Backprop for this simple network architecture is a special case of ***reverse-mode auto-differentiation:***




$$\boxed{y = f(x_1, x_2) = \ln(x_1) + x_1 x_2 - \sin(x_2)}$$

**Forward Primal Trace**

| | | |
|---|---|---|
| $v_{-1}$ | $= x_1$ | $= 2$ |
| $v_0$ | $= x_2$ | $= 5$ |
| $v_1$ | $= \ln v_{-1}$ | $= \ln 2$ |
| $v_2$ | $= v_{-1} \times v_0$ | $= 2 \times 5$ |
| $v_3$ | $= \sin v_0$ | $= \sin 5$ |
| $v_4$ | $= v_1 + v_2$ | $= 0.693 + 10$ |
| $v_5$ | $= v_4 - v_3$ | $= 10.693 + 0.959$ |
| $y$ | $= v_5$ | $= 11.652$ |

**Reverse Adjoint (Derivative) Trace**

| | | | |
|---|---|---|---|
| $\bar{x}_1$ | $= \bar{v}_{-1}$ | | $= \mathbf{5.5}$ |
| $\bar{x}_2$ | $= \bar{v}_0$ | | $= \mathbf{1.716}$ |
| $\bar{v}_{-1}$ | $= \bar{v}_{-1} + \bar{v}_1 \frac{\partial v_1}{\partial v_{-1}}$ | $= \bar{v}_{-1} + \bar{v}_1 / v_{-1}$ | $= 5.5$ |
| $\bar{v}_0$ | $= \bar{v}_0 + \bar{v}_2 \frac{\partial v_2}{\partial v_0}$ | $= \bar{v}_0 + \bar{v}_2 \times v_{-1}$ | $= 1.716$ |
| $\bar{v}_{-1}$ | $= \bar{v}_2 \frac{\partial v_2}{\partial v_{-1}}$ | $= \bar{v}_2 \times v_0$ | $= 5$ |
| $\bar{v}_0$ | $= \bar{v}_3 \frac{\partial v_3}{\partial v_0}$ | $= \bar{v}_3 \times \cos v_0$ | $= -0.284$ |
| $\bar{v}_2$ | $= \bar{v}_4 \frac{\partial v_4}{\partial v_2}$ | $= \bar{v}_4 \times 1$ | $= 1$ |
| $\bar{v}_1$ | $= \bar{v}_4 \frac{\partial v_4}{\partial v_1}$ | $= \bar{v}_4 \times 1$ | $= 1$ |
| $\bar{v}_3$ | $= \bar{v}_5 \frac{\partial v_5}{\partial v_3}$ | $= \bar{v}_5 \times (-1)$ | $= -1$ |
| $\bar{v}_4$ | $= \bar{v}_5 \frac{\partial v_5}{\partial v_4}$ | $= \bar{v}_5 \times 1$ | $= 1$ |
| $\bar{v}_5$ | $= \bar{y}$ | $= 1$ | |

# Auto-differentiation

- Given a function, computes its partial derivatives
- Compute all of the partial derivatives of a function with (nearly) same computation runtime [Griewank ’89, Baur and Strassen ’83]
- Backbone of (applied) machine learning: Pytorch, Tensorflow, …

# Example of Computation Graph

$$f(w_1, w_2) = \left( \sin\left(\frac{2\pi w_1}{w_2}\right) + \underbrace{\frac{3w_1}{w_2} - \exp(2w_2)}_{z_4} \right) \cdot \left( \underbrace{\frac{3w_1}{w_2} - \exp(2w_2)}_{z_4} \right)$$

**Input**: $z_0 = (w_1, w_2)$

$z_1 = \frac{w_1}{w_2}$

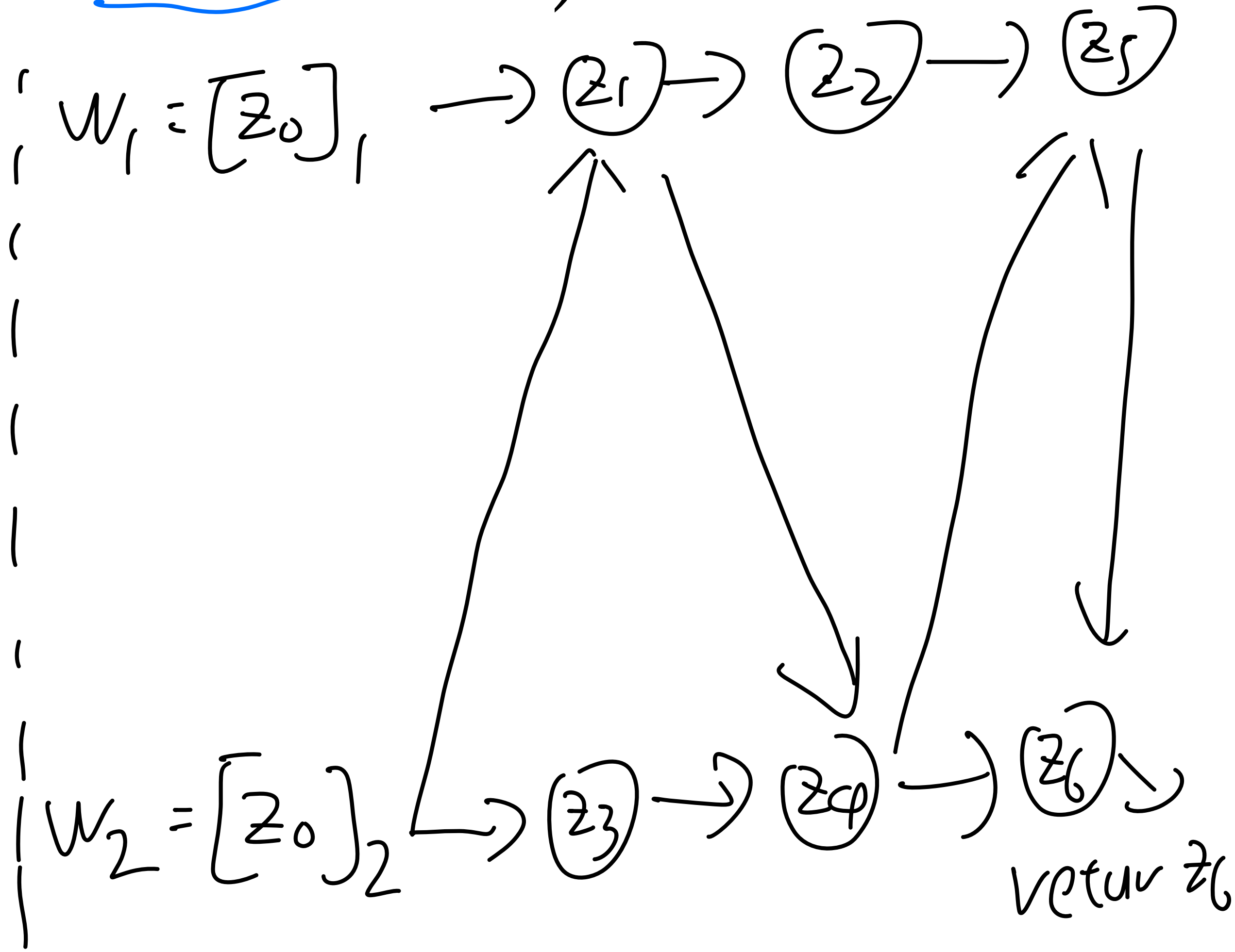
$z_2 = \sin(2\pi z_1)$

$z_3 = \exp(2w_2)$

$z_4 = 3z_1 - z_3$

$z_5 = z_2 + z_4$

$z_6 = z_4 \cdot z_5$



# Computation Model

exp, sin

- Given access to a set of differentiable real functions $h \in \mathcal{H}$
- Use functions in $\mathcal{H}$ to create intermediate variables.
- Evaluation trace:
  - All intermediate variables will be scalars; each corresponds to a node.
  - Input $z_0 = w \in \mathbb{R}^d$. $[z_0]_1 = w_1, [z_0]_2 = w_2, \ldots, [z_0]_d = w_d$
  - Step 1: $z_1 = h_1$ (a subset of variables in $w$)
  - ….  $z_2 = h_2($ ______ __ ___ $w, z_1)$
  - Step t: $z_t = h_t$ (a subset of variables in $z_1, \ldots, z_{t-1}, w$)
  - …
  - Step T: $z_T = h_T$ (a subset of variables in $z_1, \ldots, z_{T-1}, w$)
  - **Return:** $z_T$

($h_1, \ldots, h_T \in \mathcal{H}$ )

# Computation Model

- Every $h \in \mathscr{H}$ is one of the following:
  - Type 1: An affine transformation of the inputs

    $3z_1 - z_3$, $z_2 + z_5$, $z_1 + 6$

  - Type 2: A product of variables, to some power

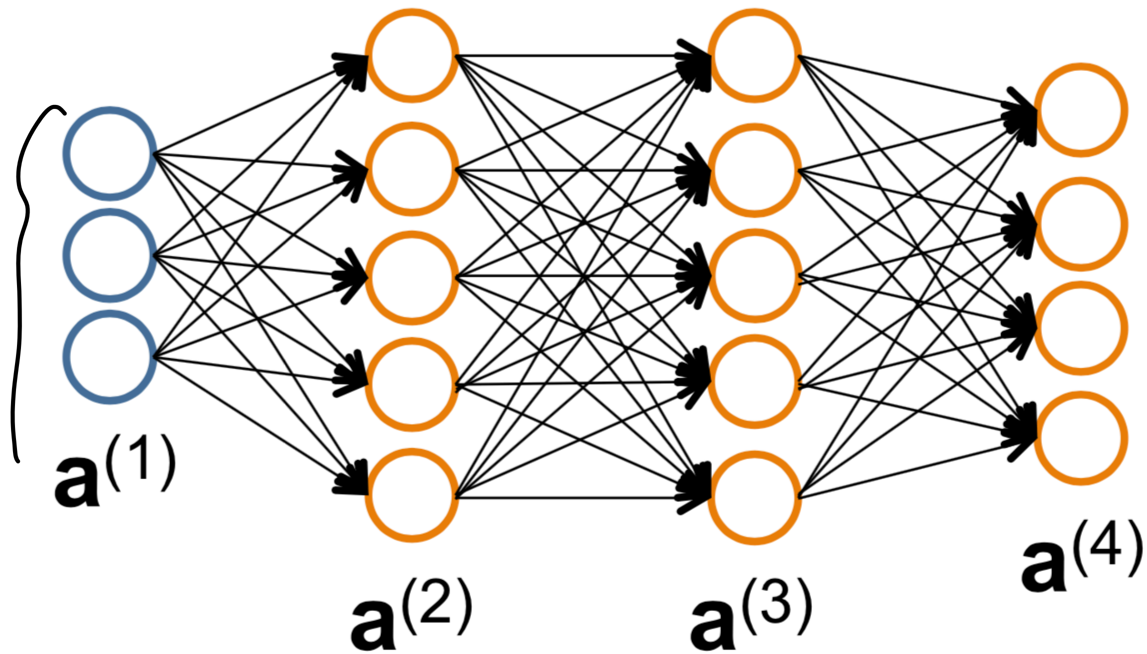
    $w_1/w_2 = w_1 \cdot w_2^{-1}$, $z_4 \cdot z_5$, $z_7 = z_1^4 z_2^6 \cdots$

  - Type 3: A fixed set of one dimensional differentiable functions: $\sin(\cdot), \cos(\cdot), \exp(\cdot), \log(\cdot), \ldots$
    - We assume we can easily compute the derivatives for each of this functions.

    - Type 3 can be approximated by Type 1 and Type 2, using polynomials.

# Neural Network Example

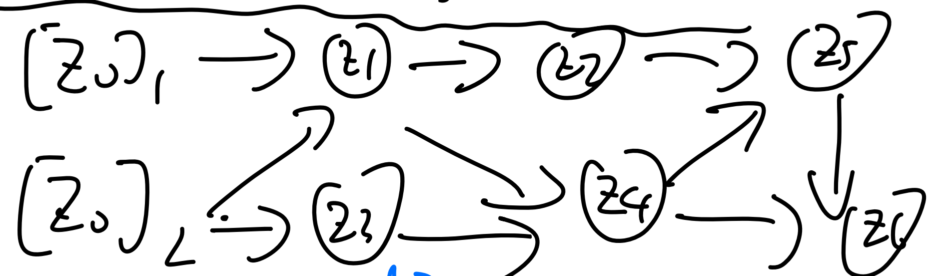
X
constant



# Reverse Mode of Automatic Differentiation

**Goal**: Compute partial derivatives of $f(w)$, i.e., $df/dw$.

- Step 1: computer $f(w)$ and store in memory all intermediate variables $z_1, \ldots, z_T$




$T = 6$

- Step 2: Initialize: $\dfrac{dz_T}{dz_T} = 1.$
- Step 3: For $t = T, T-1, \ldots, 0$
  - $$\frac{dz_T}{dz_t} = \sum_{c \text{ is a child of } t} \frac{dz_T}{dz_c} \cdot \frac{\partial z_c}{\partial z_t}$$

  (Child: a node $z_t$ directly points to)
- Step 4: Return $\dfrac{dz_T}{dz_0} = \dfrac{df}{dw}$

(1) $\dfrac{dz_6}{dz_6} = 1$

(2) $\dfrac{dz_6}{dz_5} = \dfrac{dz_6}{dz_6} \cdot \dfrac{\partial z_6}{\partial z_5}$

(3) $\dfrac{dz_6}{dz_4} = \dfrac{dz_6}{dz_5} \cdot \dfrac{\partial z_5}{\partial z_4} + \dfrac{dz_6}{dz_6} \cdot \dfrac{\partial z_6}{\partial z_4}$

(4) $\dfrac{dz_6}{dz_3} = \dfrac{dz_6}{dz_4} \cdot \dfrac{\partial z_4}{\partial z_3}$

(5) $\dfrac{dz_6}{dz_2} = \dfrac{dz_6}{dz_5} \cdot \dfrac{\partial z_5}{\partial z_2}$

(6) $\dfrac{dz_6}{dz_1} = \dfrac{dz_6}{dz_4} \cdot \dfrac{\partial z_4}{\partial z_1} + \dfrac{dz_6}{dz_2} \cdot \dfrac{\partial z_2}{\partial z_1}$

# Time Complexity

**Theorem (Baur and Strassen '83, Griewak '89):** Assume every $h$ is specified as in our computational model. For $h(\cdot)$ of type 3, assume we can compute the derivative $h'(z)$ in time as the same order of computing $h(z)$. Let $T$ denote the time to compute $f(w)$. Then the reverse mode computes $df/dw$ in time $O(T)$.

$C(1)$

Pf: (1) Time: count edges

(2) correctness: suppose $\frac{dz_T}{dz_c}$ already computed

(c is a child of t) $\Rightarrow$ we can $\frac{dz_T}{dz_t}$

$\Rightarrow$ need to prove we can $\frac{\partial z_c}{\partial z_t}$

type 1 $\Rightarrow$ coefficient of affine transformation

type 2 $\Rightarrow$ $\frac{\partial z_c}{\partial z_t} = \frac{z_c}{z_t} \cdot \alpha$,

$z_5 = z_1 \cdot z_2^2 \to \alpha$

$\Rightarrow \frac{\partial z_5}{\partial z_2} = \frac{z_5}{z_2} \cdot 2$

type 3 $\Rightarrow z_c = h(z_t) \Rightarrow \frac{\partial z_c}{\partial z_t} = h'(z_t)$

# Time Complexity

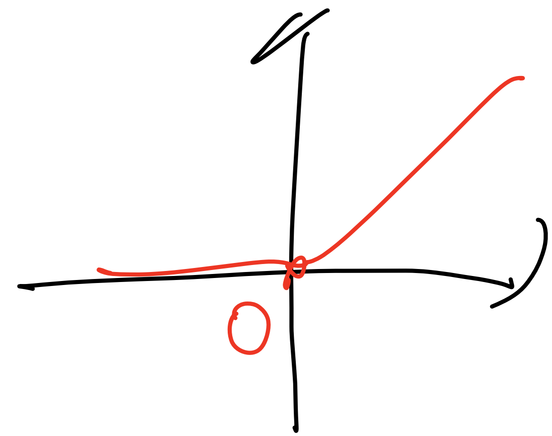
# Clarke Differential

# Subdifferential and Subgradient

**Definition:** Given $f : \mathbb{R}^d \to \mathbb{R}$, for every $x$, the subdifferential set is defined as $\partial_s f(x) \triangleq \{s \in \mathbb{R}^d : \forall x' \in \mathbb{R}^d, f(x') \geq f(x) + s^\top (x' - x)\}$. The elements in the subdifferential set are subgradients.

$g_t \in \partial_s f(x)$

$x_{t+1} \leftarrow x_t - \eta g_t$




$\partial_s f(0) = [0,1]$

# Subdifferential and Subgradient

**Definition:** Given $f : \mathbb{R}^d \to \mathbb{R}$, for every $x$, the subdifferential set is defined as $\partial_s f(x) \triangleq \{s \in \mathbb{R}^d : \forall x' \in \mathbb{R}^d, f(x') \geq f(x) + s^\top(x' - x)\}$. The elements in the subdifferential set are subgradients.

- If $f$ convex $\rightarrow$ $\partial_s f$ exists everywhere
- If $f$ convex & differentiable

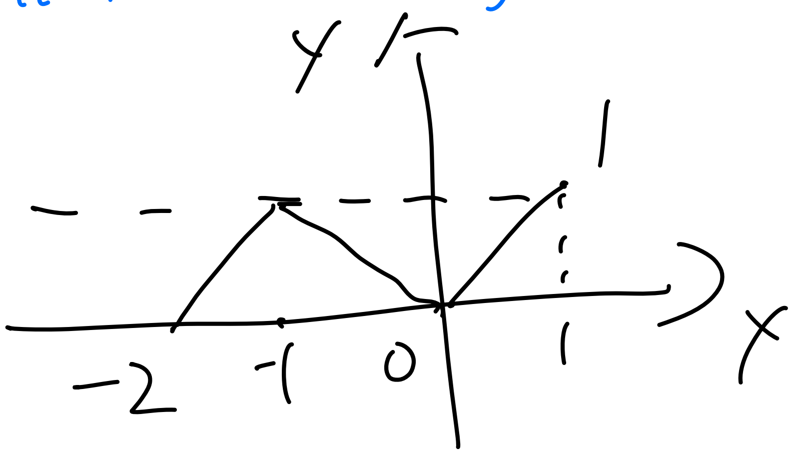
$$\partial_s f = \{\nabla f\}$$

- $O\left(\frac{1}{\sqrt{T}}\right)$, $T$ := # of iters

# Subdifferential is not enough

**Definition:** Given $f : \mathbb{R}^d \to \mathbb{R}$, for every $x$, the subdifferential set is defined as
$\partial_s f(x) \triangleq \{s \in \mathbb{R}^d : \forall x' \in \mathbb{R}^d, f(x') \geq f(x) + s^\top (x' - x)\}$. The elements in the subdifferential set are subgradients.

Problem: loss for NN is not convex




$x = -1$

we need $s$ s.t. $\forall x'$

$f(x') \geq 1 + s \cdot (x' - (-1))$

- choose $x' = -2$

  $0 \geq 1 + s \cdot (-1) \Rightarrow s \geq 1$

- choose $x' = 1$

  $1 \geq 1 + s(2) \Rightarrow s \leq 0$

# Clarke Differential

**Definition:** Given $f : \mathbb{R}^d \to \mathbb{R}$, for every $x$, the Clark differential is defined as

$$\partial f(x) \triangleq \text{conv}\left(\{s \in \mathbb{R}^d : \exists \{x_i\}_{i=1}^{\infty} \to x, \{\nabla f(x_i)\}_{i=1}^{\infty} \to s\}\right).$$

The elements in the subdifferential set are subgradients.

# When does Clarke differential exists

**Definition (Locally Lipschitz)**: $f : \mathbb{R}^d \to \mathbb{R}$ is locally Lipchitz if $\forall x \in \mathbb{R}^d$, there exists a neighborhood $S$ of $x$, such that $f$ is Lipchitz in $S$.