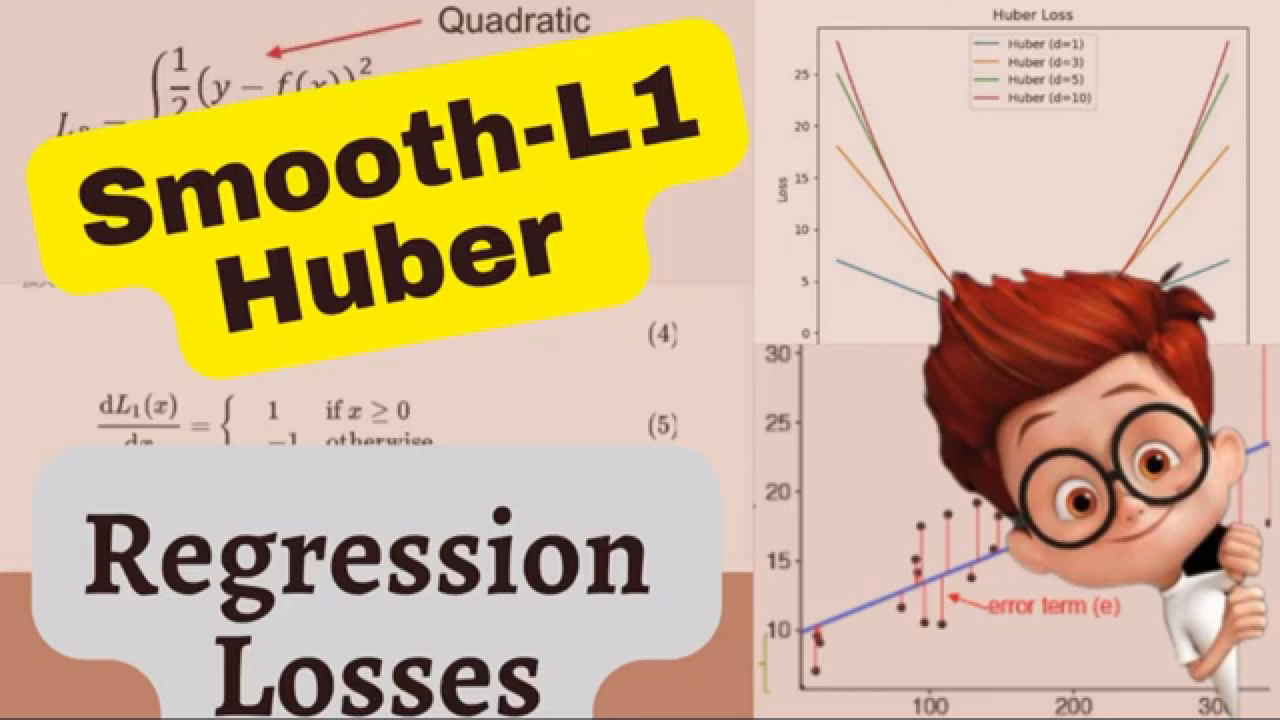

Quadratic
Smooth-L1
Huber
(4)
(5)
Regression
Losses
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Huber (d=1)
Huber (d=3)
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Loss
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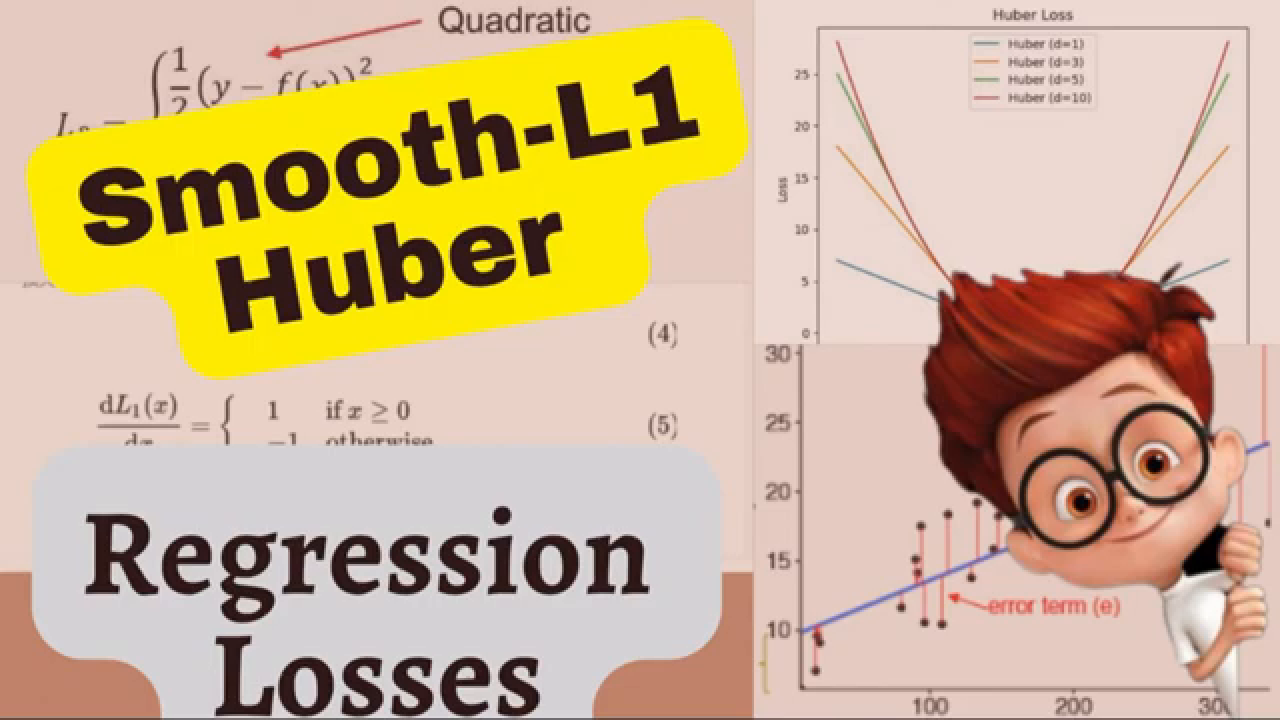
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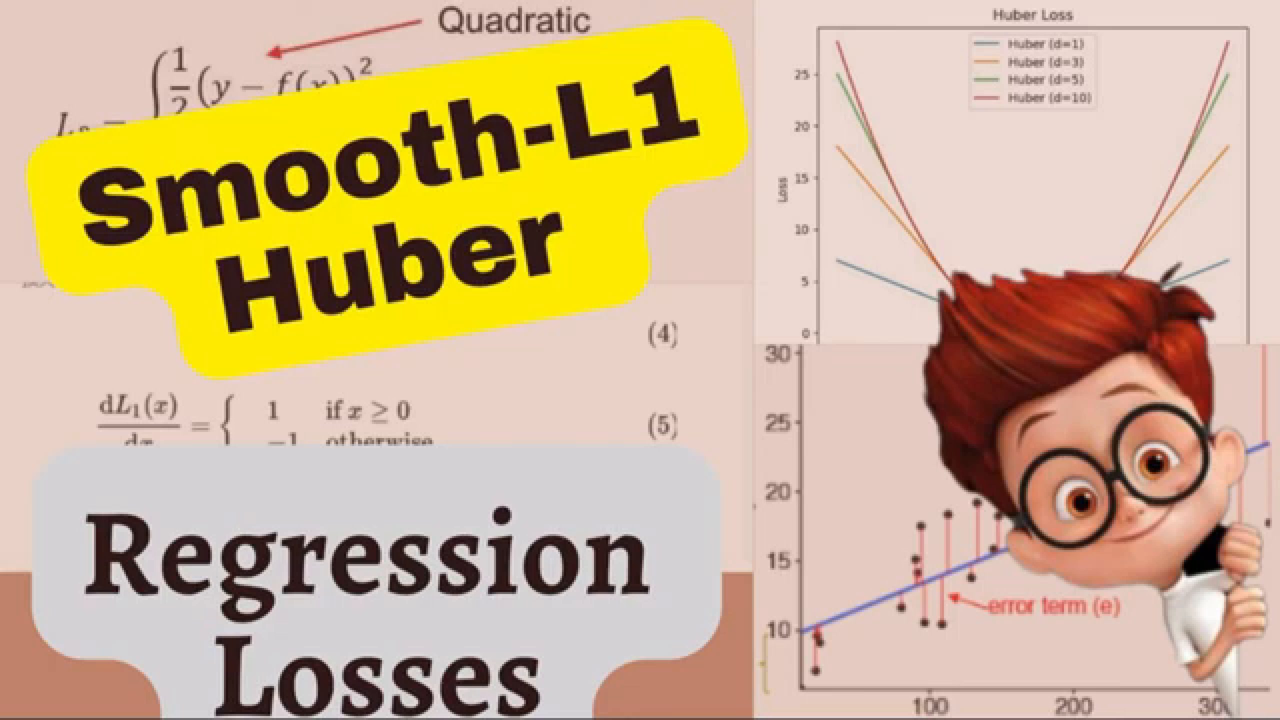
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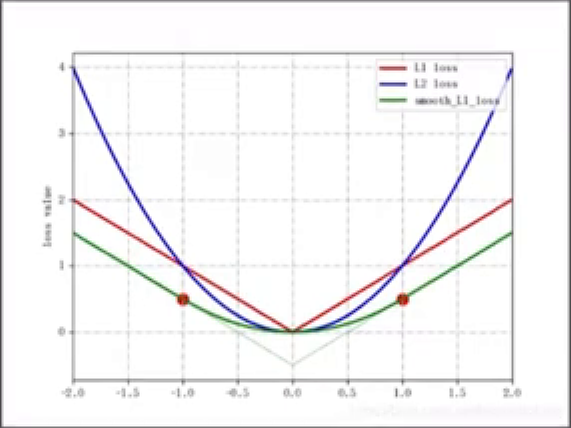

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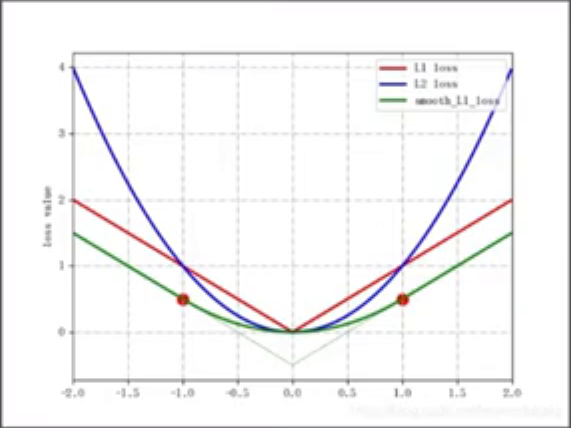

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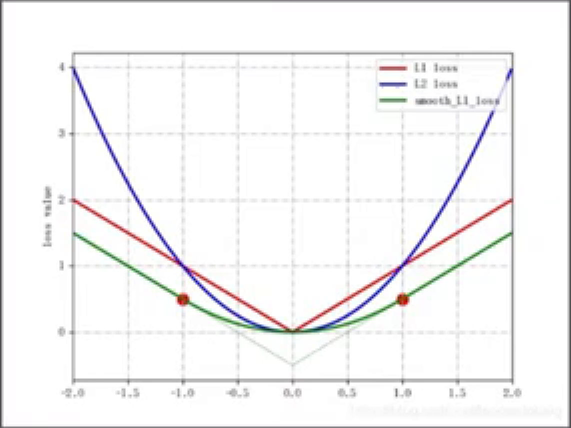

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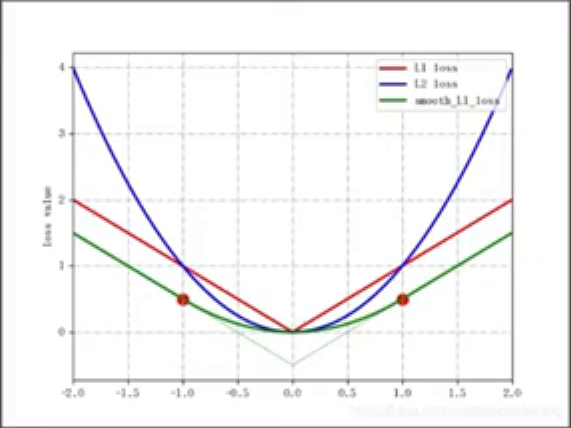

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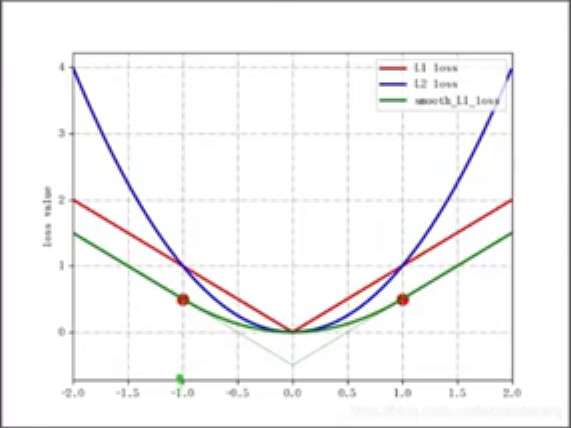

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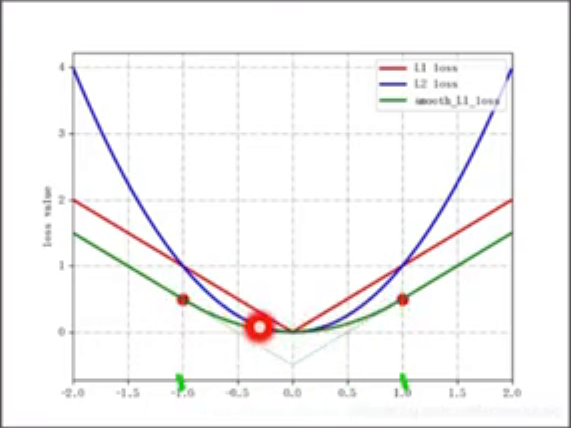

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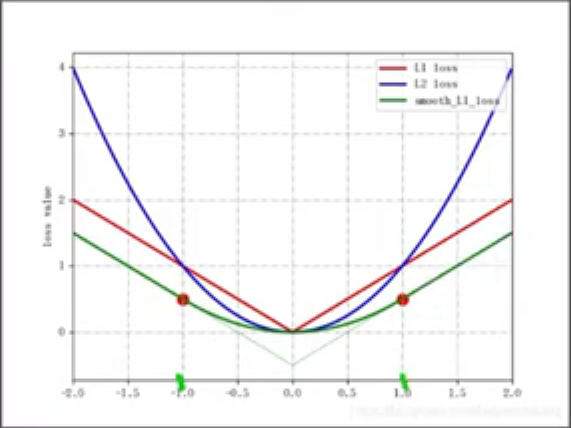

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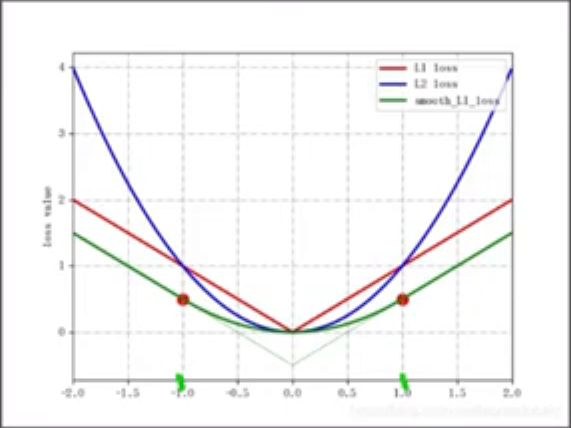

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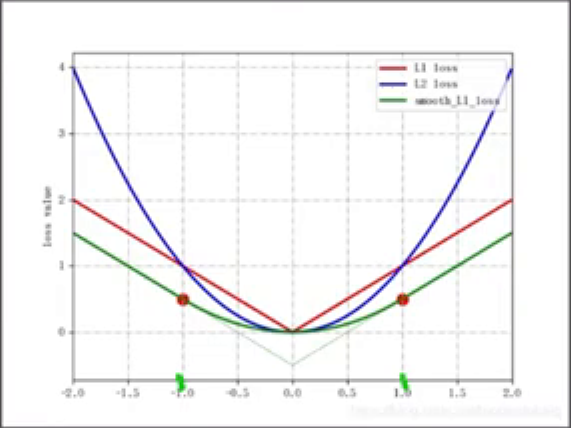

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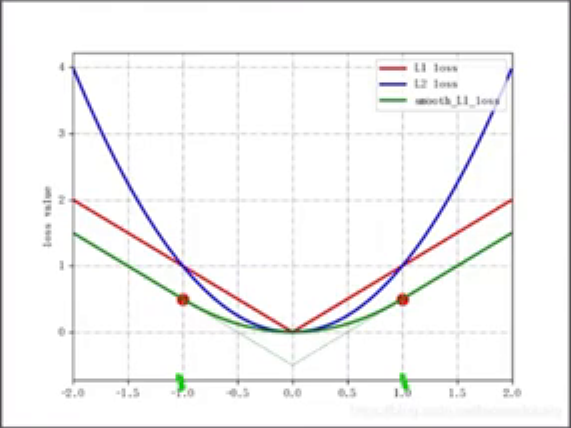

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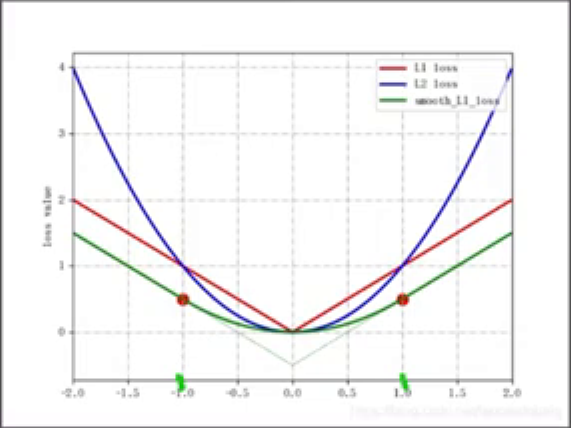

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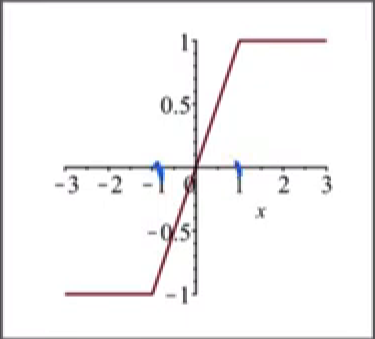

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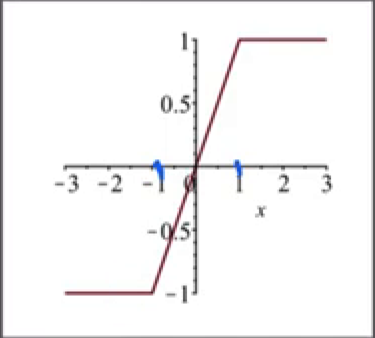

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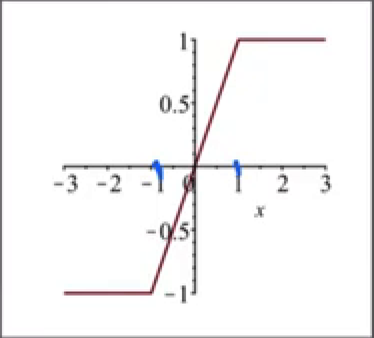

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Dynamic SmoothL1 Loss

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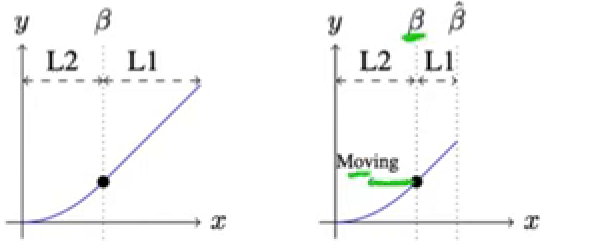
Self-Adjusting Smooth L1 Loss



(a) Smooth L1 (b) Self-Adjusting Smooth L1

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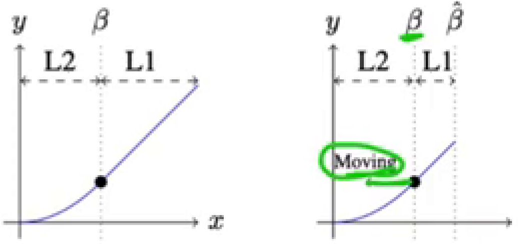

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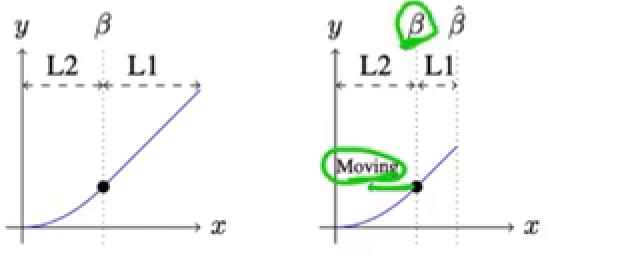

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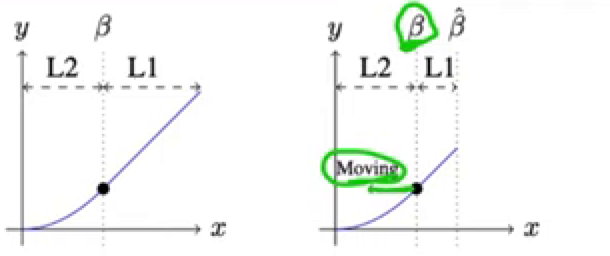

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Huber Loss

https://github.com › torch › issues

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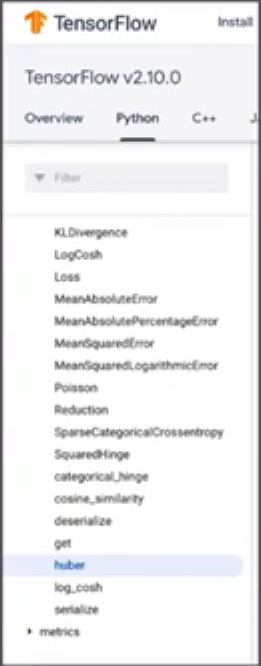

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Smooth-L1

beta = delta

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Huber = beta (S-L1)

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$$l_n = \begin{cases} 0.5(x_n - y_n)^2/beta, & \text{if } |x_n - y_n| < beta \\ |x_n - y_n| - 0.5 * beta, & \text{otherwise} \end{cases}$$

Smooth-L1

$$l_n = \begin{cases} 0.5(x_n - y_n)^2, & \text{if } \underline{|x_n - y_n| < delta} \\ delta * (|x_n - y_n| - 0.5 * delta), & \text{otherwise} \end{cases}$$

Huber = beta (S-L1)

Huber Loss

$$l_n = \begin{cases} 0.5(x_n - y_n)^2 / beta, & \text{if } |x_n - y_n| < beta \\ |x_n - y_n| - 0.5 * beta, & \text{otherwise} \end{cases}$$

Smooth-L1

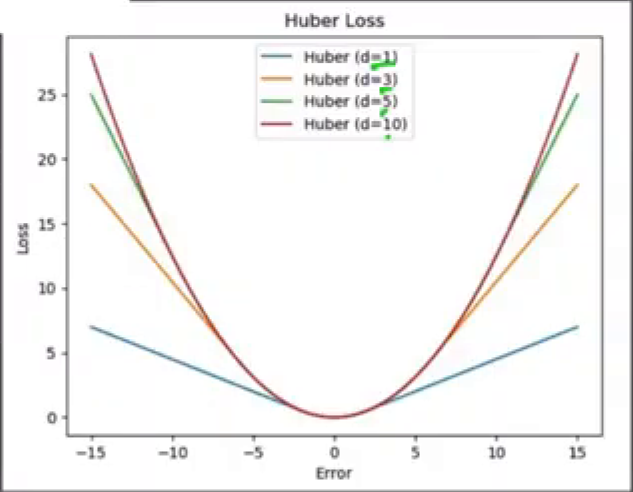
$$l_n = \begin{cases} 0.5(x_n - y_n)^2, & \text{if } |x_n - y_n| < delta \\ delta * (|x_n - y_n| - 0.5 * delta), & \text{otherwise} \end{cases}$$

Huber = beta (S-L1)

3

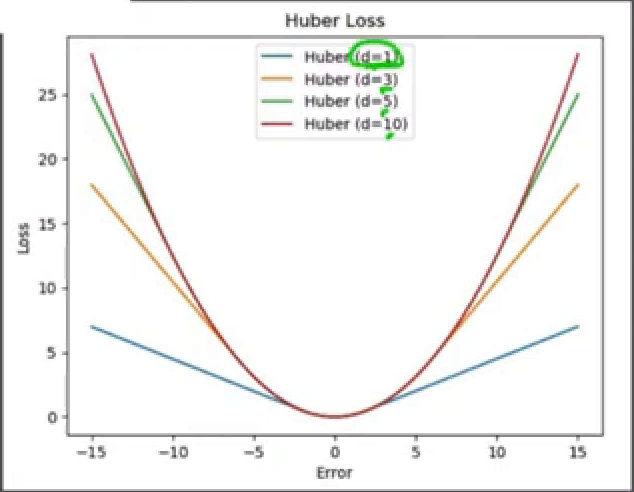
Huber Loss

$$l_n = \begin{cases} 0.5(x_n - y_n)^2, & \text{if } |x_n - y_n| < delta \\ delta * (|x_n - y_n| - 0.5 * delta), & \text{otherwise} \end{cases}$$



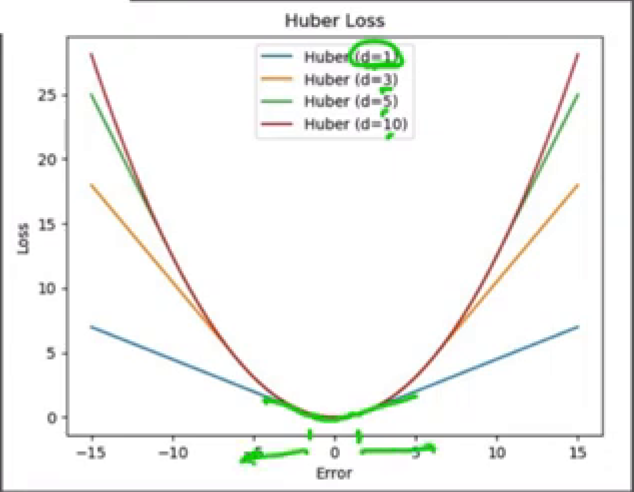
Huber Loss

$$l_n = \begin{cases} 0.5(x_n - y_n)^2, & \text{if } |x_n - y_n| < delta \\ delta * (|x_n - y_n| - 0.5 * delta), & \text{otherwise} \end{cases}$$



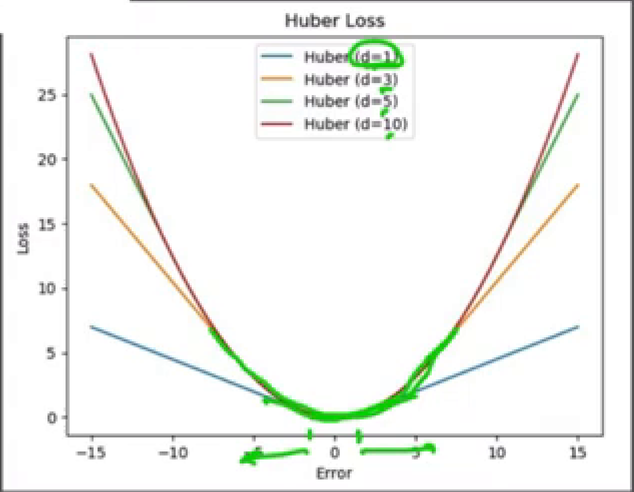
Huber Loss

$$l_n = \begin{cases} 0.5(x_n - y_n)^2, & \text{if } |x_n - y_n| < delta \\ delta * (|x_n - y_n| - 0.5 * delta), & \text{otherwise} \end{cases}$$



Huber Loss

$$l_n = \begin{cases} 0.5(x_n - y_n)^2, & \text{if } |x_n - y_n| < delta \\ delta * (|x_n - y_n| - 0.5 * delta), & \text{otherwise} \end{cases}$$



Implementation

```
def smoothl1loss(x, y):
    if abs(x-y)<1: return 1/2*(x-y)**2
    else: return abs(x-y)-1/2
```