

# Final exam review

What did we learn in this course?

1. Python basics:

- [Python\\_1.ipynb](#)
- [Python\\_2.ipynb](#)

2. Numpy basics:

- [NumpyTutorial.ipynb](#)

3. Linear Regression by vector derivatives:

- [LinearModels.ipynb](#),
- [PlaneFitProblem](#),
- [Hessians](#),
- [Practice Problems for Midterm 1](#),

4. Optimization by Gradient descent:

- [ContinuousOptimization.ipynb](#)

5. 1-Layer Neural Network: [Perceptron3.ipynb](#)

6. Pre-midterm review: [Practice Problems](#)

minimize

Quadratic form  
of vectors

Any vector expression  
Quadratic  
take its derivative  
and equate it to zero

Decision Theory:

- Lecture notes: [decision-theory.pdf](#). Additional resources:
- [Chapter 2 of MLStory book](#)

$$\frac{\partial}{\partial \underline{x}} \left[ \underline{x}^T \underline{Q} \underline{x} + \underline{b}^T \underline{x} + c \right] \rightarrow \underline{x}^T (\underline{Q} + \underline{Q}^T) + \underline{b}^T + 0 = 0$$

$$\underline{x}^T \hookrightarrow \underline{b}^T (\underline{Q} + \underline{Q}^T)^{-1}$$

$$\underline{x} = -(\underline{Q} + \underline{Q}^T)^{-T} \underline{b}$$

Bayes Rule

Question:

Given two random variables  $X$  and  $Y$  specify the relationship between  $P(X|Y)$  and  $P(Y$

Answer

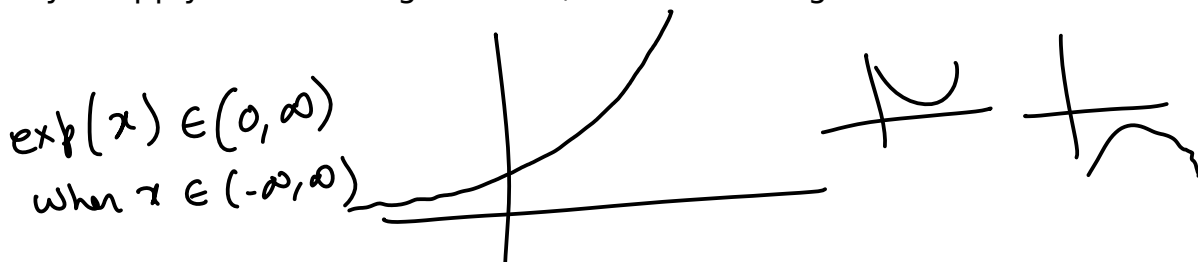
$P(Y|X)P(X)$

Regularization can be interpreted as application for Bayes theorem

(Maximum-a-posterior estimate)  
MAP estimate

$$\begin{aligned} \arg \min_w L(D; w) + \lambda \|w\|_2^2 &\longleftrightarrow \arg \max_w \underbrace{P(w|D)}_{\in [0, 1]} \\ \arg \max_w \underbrace{-L(D; w) - \lambda \|w\|_2^2}_{\in (-\infty, \infty)} \end{aligned}$$

In optimization, the optimal value/argument stays unchanged if you apply an increasing function. If you apply a decreasing function, the max changes to min and min changes to max.



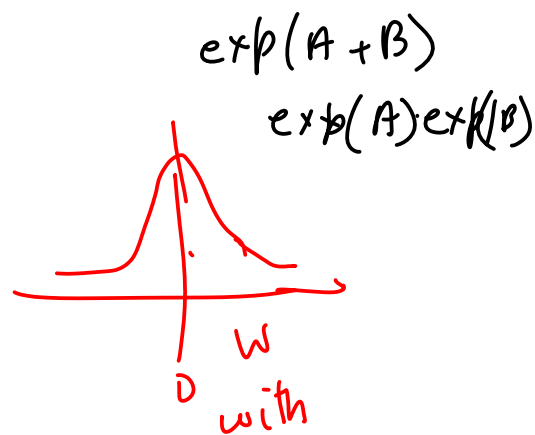
$$\arg \max_w \underbrace{\frac{1}{Z} \exp(-L(D; w) - \lambda \|w\|_2^2)}_{P(w|D) \text{ posterior}} \in [0, \infty)$$

where  $Z$  is a normalization factor so that

$$\sum_w \exp(\dots) = Z$$

Gaussian dist

$$\arg \max_w \underbrace{\frac{1}{Z}}_{\text{Evidence}} \underbrace{\exp(-L(D; w))}_{P(D|w) \text{ likelihood}} \underbrace{\exp(-\frac{\lambda}{2} \|w\|_2^2)}_{P(w) \text{ prior}}$$



$$\text{STD} \cdot \frac{1}{\lambda} = 2\sigma^2$$

$$\Rightarrow \sigma = \frac{1}{2\sqrt{\lambda}}$$

# Vector Jacobian product

Reverse mode differentiation

And it assumes the final output of the computation graph is a scalar (true for a loss function)

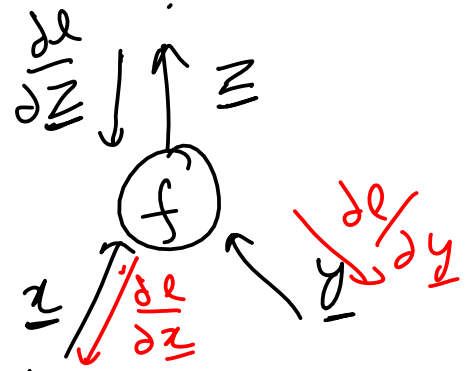
scalar (true for a loss function)

$$\frac{\partial l}{\partial \underline{x}} = \frac{\partial l}{\partial \underline{z}} \frac{\partial \underline{z}}{\partial \underline{x}} \leftarrow \text{Jacobian}$$

The responsibility of VJP function is to compute

$$\frac{\partial l}{\partial \underline{x}}, \frac{\partial l}{\partial \underline{y}} \text{ given } \frac{\partial l}{\partial \underline{z}} \leftarrow \text{vector}$$

and you can use  $\underline{x}, \underline{y}$   
 $f(\underline{x}, \underline{y})$



Examples

$$f(\underline{x}, \underline{y}) = \underline{x}^T \underline{x} + \underline{y}$$

Find the VJP

Assume an eventual scalar function

$$\frac{\partial}{\partial \underline{x}} l(f(\underline{x}, \underline{y})) = \frac{\partial l}{\partial \underline{f}} \frac{\partial \underline{f}}{\partial \underline{x}} = \frac{\partial l}{\partial \underline{f}} (I_{n \times n} + 0_{n \times n})$$

$$= \frac{\partial l}{\partial \underline{f}} = \frac{\partial l}{\partial \underline{z}}$$

$$\frac{\partial}{\partial \underline{y}} l(f(\underline{x}, \underline{y})) = \frac{\partial l}{\partial \underline{f}} = \frac{\partial l}{\partial \underline{z}}$$

$$\frac{\partial}{\partial \underline{x}} A \underline{x} = A^T$$

$$\frac{\partial}{\partial \underline{x}} \begin{bmatrix} \underline{a}_1^T \\ \vdots \\ \underline{a}_n^T \end{bmatrix} \underline{x} = \begin{bmatrix} \underline{a}_1^T \\ \vdots \\ \underline{a}_n^T \end{bmatrix}$$

$$f(\underline{x}, \underline{y}) = \underline{x}^T \underline{y} \quad \ell \in \mathbb{R} \quad \underline{x} \in \mathbb{R} \quad \underline{y} \in \mathbb{R}$$

$$\frac{\partial}{\partial \underline{x}} \ell(f(\underline{x}, \underline{y})) = \frac{\partial \ell}{\partial f} \frac{\partial f}{\partial \underline{x}} = \frac{\partial \ell}{\partial f} \underline{y}^T$$

$$\frac{\partial}{\partial \underline{y}} \ell(f(\underline{x}, \underline{y})) = \frac{\partial \ell}{\partial f} \frac{\partial f}{\partial \underline{y}} = \frac{\partial \ell}{\partial f} \underline{x}^T$$

$$f(x) = \sin(x)$$

VJP?

$$f(x) = \frac{1}{1 + \exp(-x)}$$

VJP?

Project Convolution x

$$f(W, I) = W \otimes I$$

VJP?

$$f(\underline{x}, \underline{w}) = \frac{1}{1 + \exp(\underline{w}^T \underline{x})}$$

VJP?