REGULARIZATIONS

Introduction to Machine Learning, Artificial Intelligence and Deep Learning

Session 11

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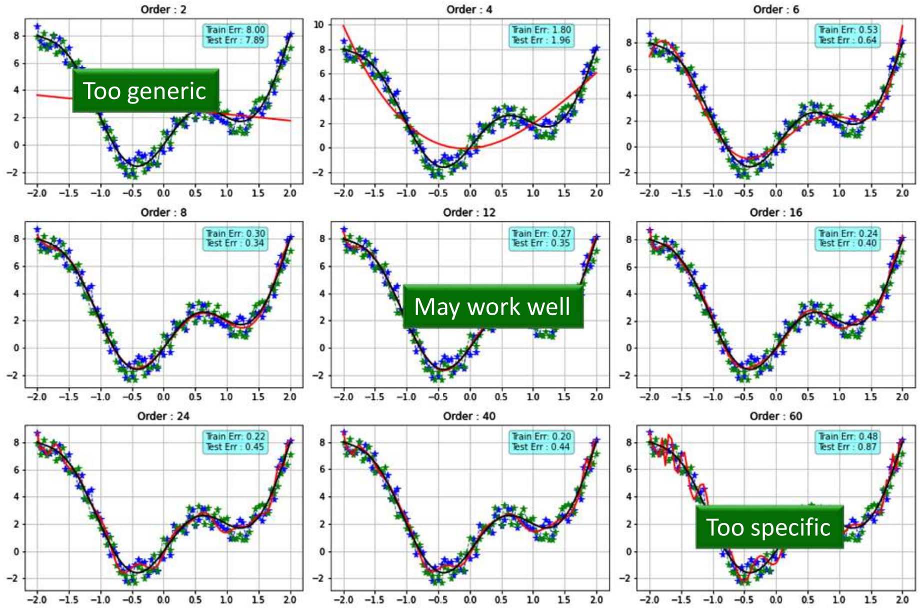
2

Agenda

- L-1, L-2
- Dropout
- Early Stopping
- Augmentation

3

Under-fitting vs. Over-fitting



Too generic

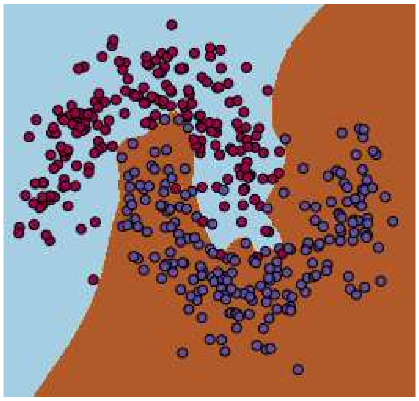
May work well

Too specific

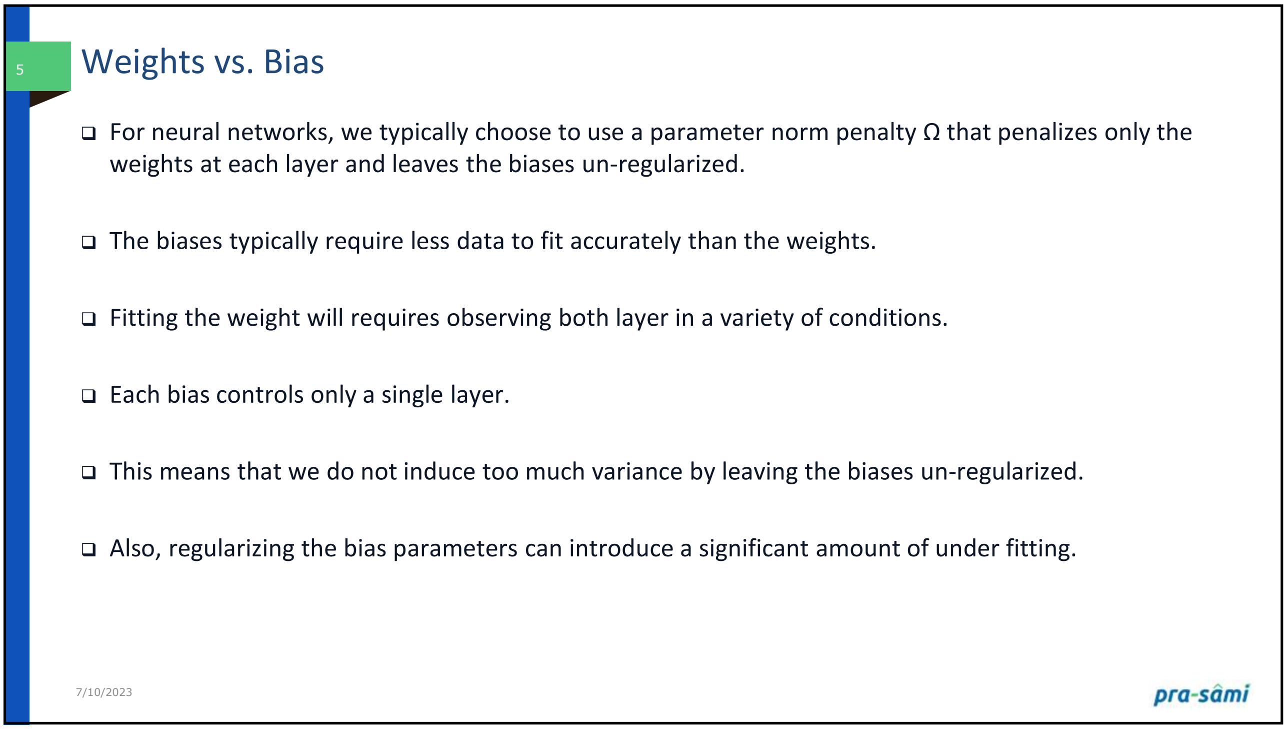
4

Regularization

- ❑ Regularization helps in avoiding over fitting by penalizing the coefficients
- ❑ In deep learning, it actually penalizes the weight matrices of the nodes
- ❑ Different Regularization Techniques in Deep Learning
  - ❖ L1 regularization
  - ❖ L2 regularizations
  - ❖ Dropouts
  - ❖ Early stopping
  - ❖ Data Augmentation



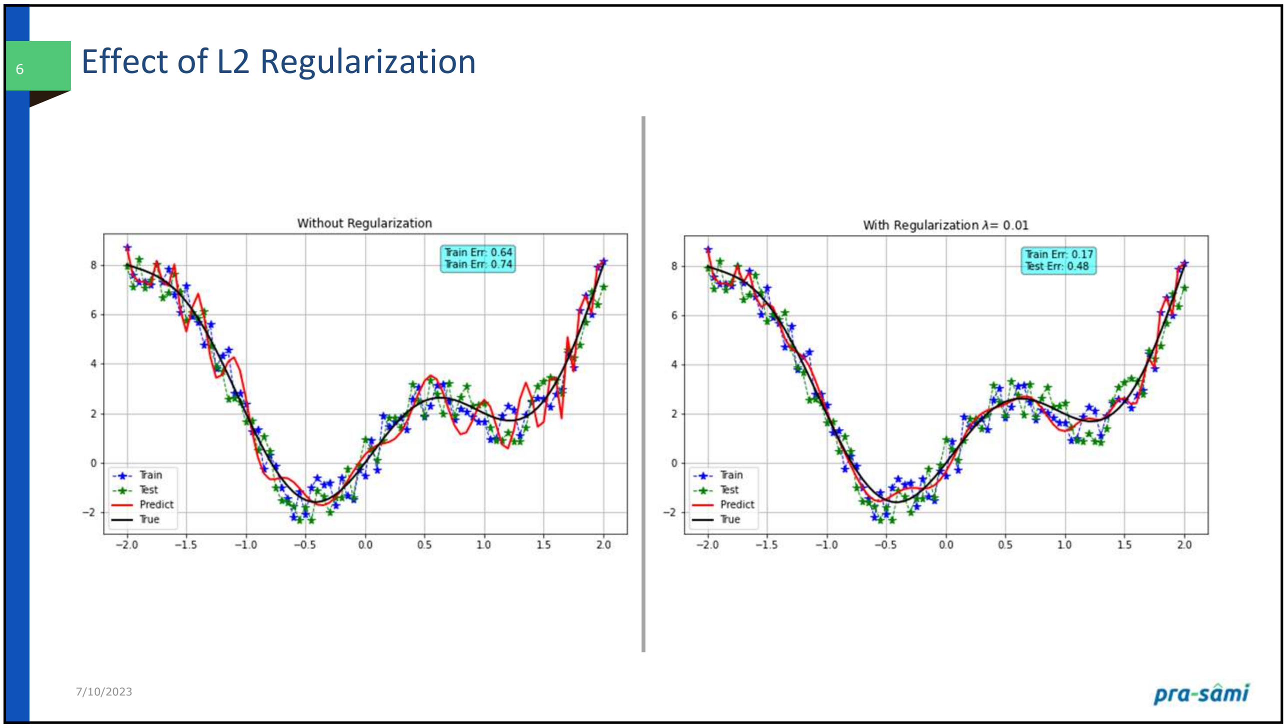
Most Libraries have tunable hyper-parameters!



5

Weights vs. Bias

- ❑ For neural networks, we typically choose to use a parameter norm penalty Ω that penalizes only the weights at each layer and leaves the biases un-regularized.
- ❑ The biases typically require less data to fit accurately than the weights.
- ❑ Fitting the weight will requires observing both layer in a variety of conditions.
- ❑ Each bias controls only a single layer.
- ❑ This means that we do not induce too much variance by leaving the biases un-regularized.
- ❑ Also, regularizing the bias parameters can introduce a significant amount of under fitting.



6

Effect of L2 Regularization

Theory – Logistic Regression – L1 & L2

- ❑ Idea is to minimize Cost Function
  - ❖ J (W, b) = $\frac{1}{m}$ * Σ ℓ (a, y)
  - ❖ = - $\frac{1}{m}$ {y * log(a) + (1-y) * log(1-a)}
- ❑ A term is added to Cost function $\frac{\lambda}{2*m} . \|W\|_2^2$
- ❑ J (W, b) = $\frac{1}{m}$ * Σ ℓ (a, y) + $\frac{\lambda}{2*m} . \|W\|_2^2$

Theory – Logistic Regression – L1 & L2

- ❑ J (W, b) = $\frac{1}{m}$ * Σ ℓ (a, y) + $\frac{\lambda}{2*m} . \|W\|_2^2$ + ~~$\frac{\lambda}{2*m} . b^2$~~
  - ❖ This is referred as L2 regularization
  - ❖ **Regularization hyperparameter λ**: It is another parameter we tune…
- ❑ $\|W\|_2^2 = \sum_{j=1}^{n} w_j^2 = W^T$ .W
- ❑ Here, we are using Euclidean Norm or L2 Norm
- ❑ Compared to W, bias b has fewer dimensions, hence, it is generally not considered
- ❑ If you add for b, ($\frac{\lambda}{2*m}$ .b^2)… that's ok too
  - ❖ Although its effect will be minimal,
  - ❖ Better to leave it alone.

9

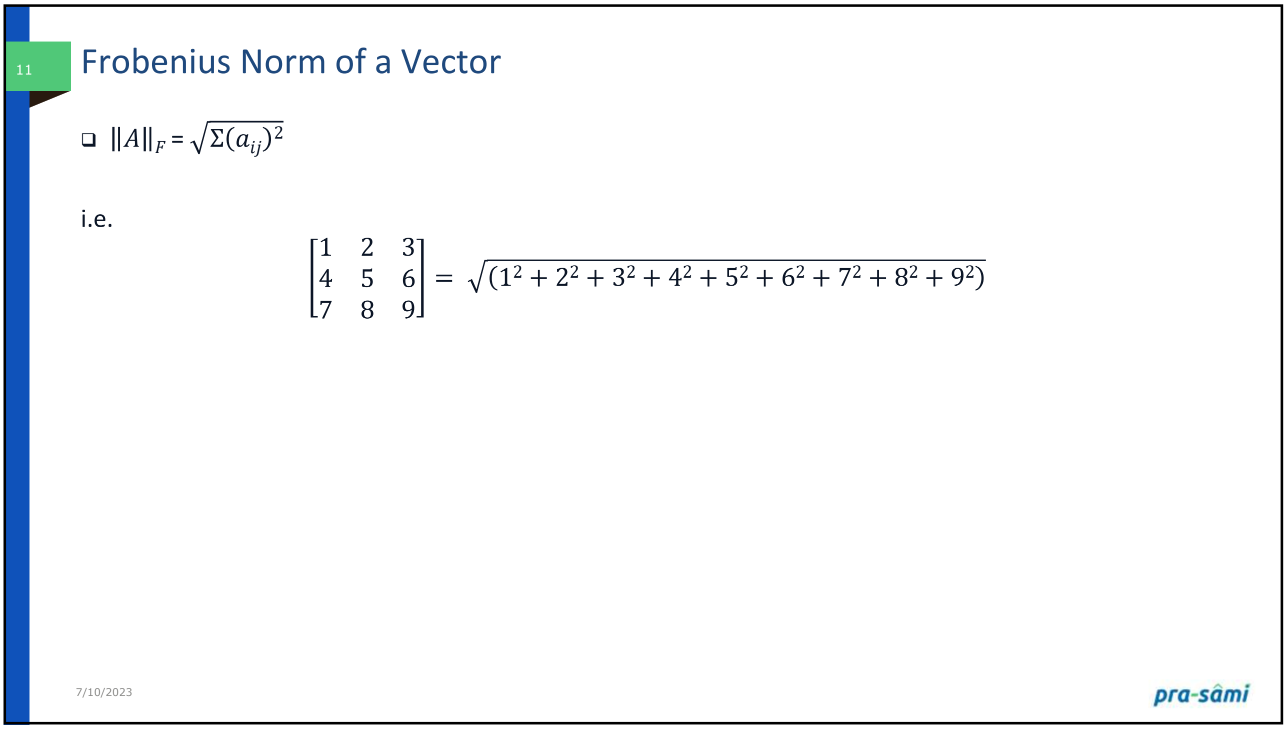
Theory – Logistic Regression – L1 & L2

- Sometimes L1 too is used
- J (W, b) = $\frac{1}{m}$ * (Σ ℓ (a, y)) + $\frac{\lambda}{2*m}$. $\|W\|_1$
- Differentation of $\frac{\lambda}{2*m}$. $\|W\|_1$ = $\frac{\lambda}{2*m}$ sign(W)
  - Will be infinitely small and will have insignificant impact on gradient descent

10

Neural Network – *Frobenius* Norm

- In neural network, we have different layers with different weights
- So we look at its cumulative effect over all layers
- Hence the Cost function
  - J (W, b) = J ($W^{[1]}$, $b^{[1]}$, $W^{[2]}$, $b^{[2]}$, $W^{[3]}$, $b^{[3]}$ ...)
  - J (W, b) = $\frac{1}{m}$ * (Σ ℓ (a, y)) + $\frac{\lambda}{2*m}$. $\sum_{l=1}^{L} \sum (w_{i,j})^{2}$
  - J (W, b) = $\frac{1}{m}$ * Σ{y * log(a) + (1-y) * log(1-a)} + $\frac{\lambda}{2*m}$. $\sum_{l=1}^{L} \|W^{[l]}\|^2$
  - Where $\|W^{[l]}\|^2{}_F = \sum_{i=1}^{n[l-1]} \sum_{j=1}^{n[l]} (w_{ij}{}^{[l]})^2$
    - W is ($n^{[l-1]}$, $n^{[l]}$) dimensional matrix
- It is called *Frobenius norm* of a matrix
- Also the Euclidean norm defined as the square root of the sum of the absolute squares of its elements



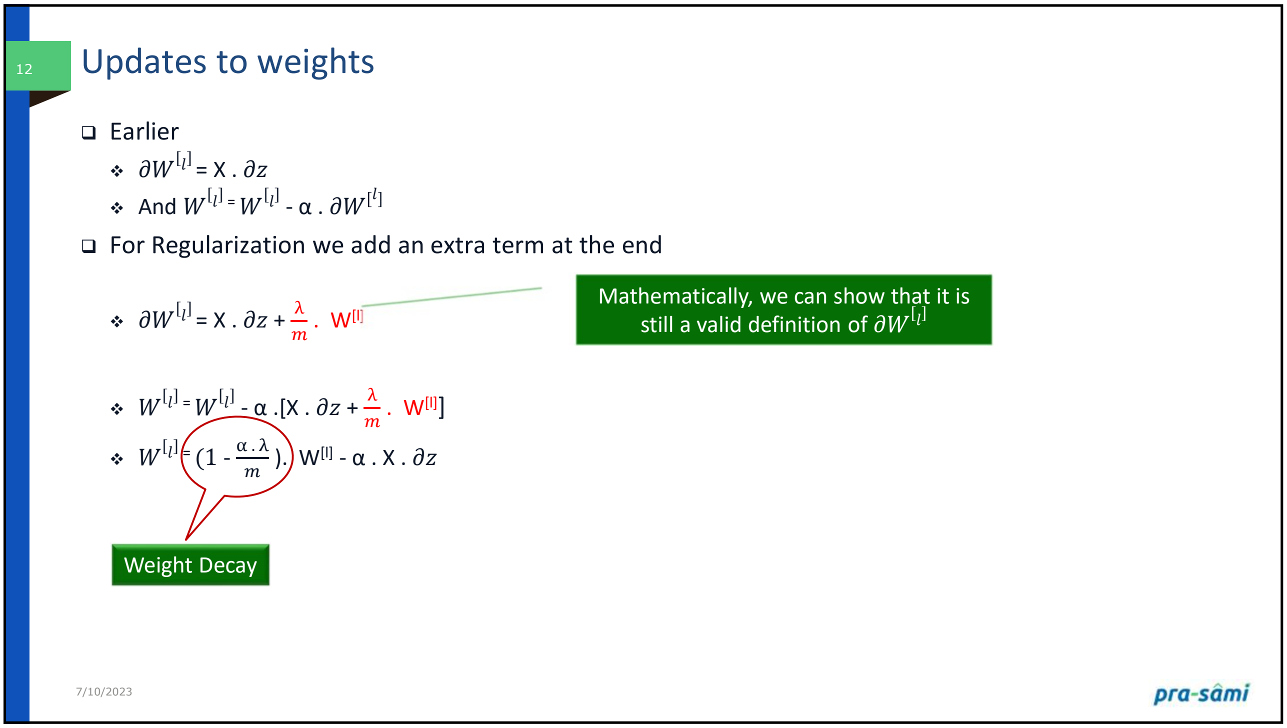
11

Frobenius Norm of a Vector

- $\|A\|_F = \sqrt{\Sigma(a_{ij})^2}$

i.e.

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} = \sqrt{(1^2 + 2^2 + 3^2 + 4^2 + 5^2 + 6^2 + 7^2 + 8^2 + 9^2)}$$



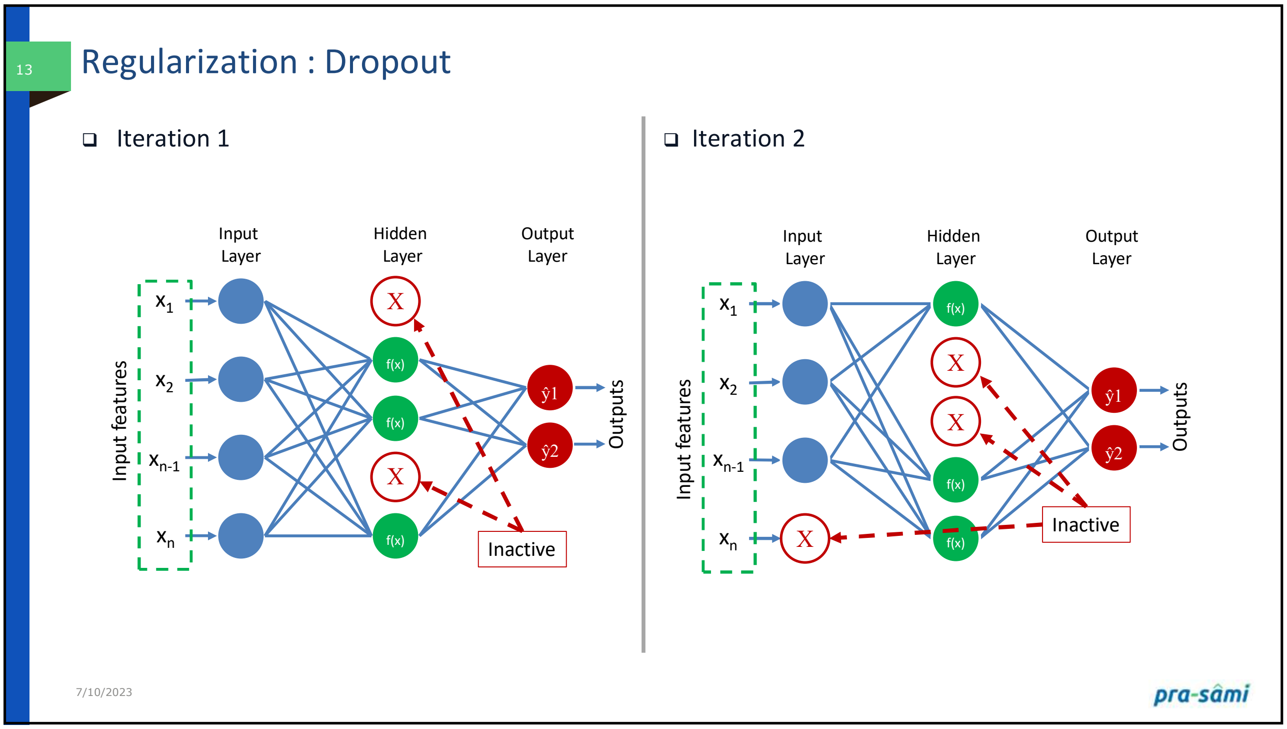
12

Updates to weights

- Earlier
  - $\partial W^{[l]}$ = X . ∂z
  - And $W^{[l]}$ = $W^{[l]}$ - α . $\partial W^{[l]}$
- For Regularization we add an extra term at the end
  - $\partial W^{[l]}$ = X . ∂z + $\frac{\lambda}{m}$. W[l]
  - $W^{[l]}$ = $W^{[l]}$ - α .[X . ∂z + $\frac{\lambda}{m}$. W[l]]
  - $W^{[l]}$ = $(1 - \frac{\alpha . \lambda}{m})$. W[l] - α . X . ∂z

Mathematically, we can show that it is still a valid definition of $\partial W^{[l]}$

Weight Decay



13

Regularization : Dropout

- ❑ Iteration 1

- ❑ Iteration 2

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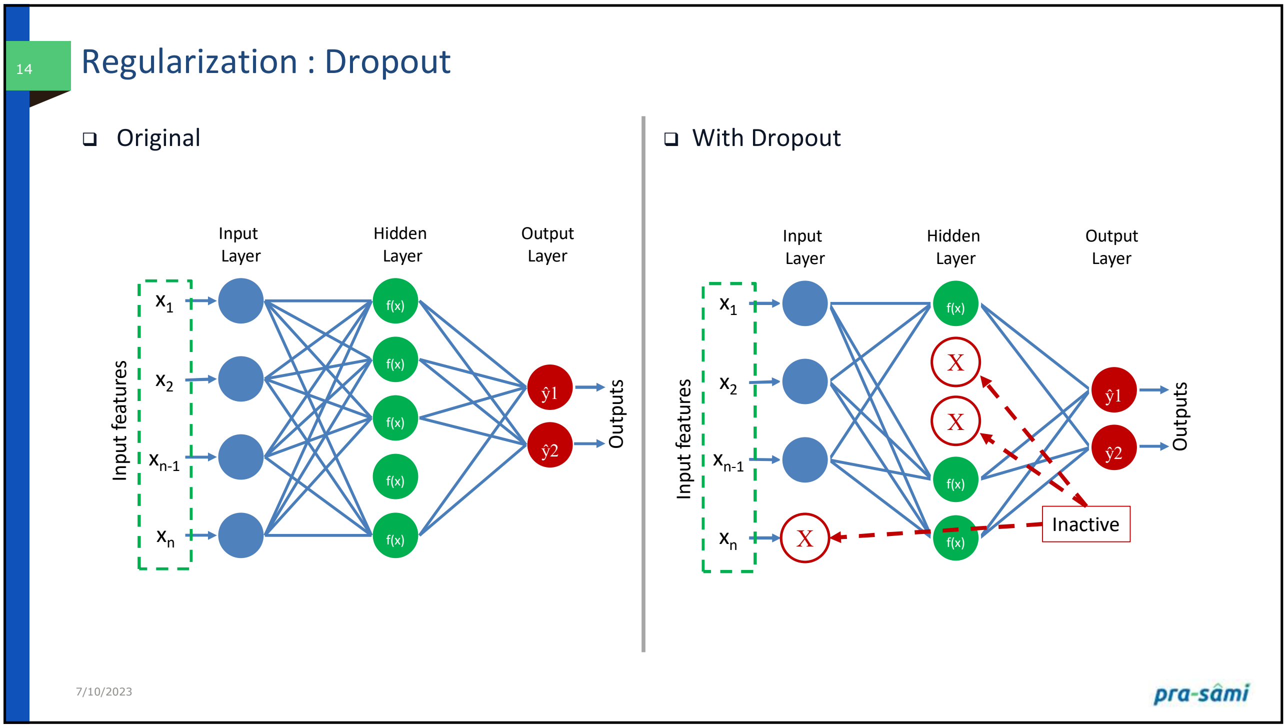

14

Regularization : Dropout

- ❑ Original

- ❑ With Dropout

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15

Regularization : Early Stopping

- ❑ How long to train the model?
- ❑ Duration of training ➔ under – fit or over – fit
- ❑ Train the model to the point where it performance on test set is best!
- ❑ Very simple and very effective

How:

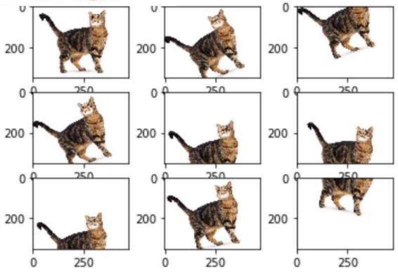
- ❑ Train the model and monitor performance
- ❑ Save weight every time the performance improves
- ❑ Stop training if performance has not improved for N epochs
- ❑ It's the last parameter to tune
  - ❖ Repeated early stopping may lead to over-fitting the validation set
  - ❖ Example : K-fold

16

Regularization : Data Augmentation

- ❑ Where limited data is available for training the model (when is it not!)
- ❑ Very effective in image identification
- ❑ Most libraries have Image Generators (parameter driven)
  - ❖ Horizontal and Vertical Shift
  - ❖ Horizontal and Vertical Flip
  - ❖ Random Rotation
  - ❖ Random Brightness / Contrast
  - ❖ Random Zoom
  - ❖ Random Noise

https://towardsdatascience.com/image-augmentation-for-deep-learning-histogram-equalization-a71387f609b2



17

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