DEEP LEARNING FOR PERCEPTION

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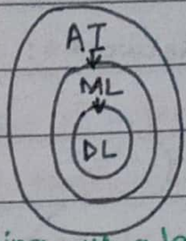


→ Deep Learning
- Deep → Deep forest
- Learning → Neural Networks → GANS, NLP

→ 3 Types of learning in ML
- Supervised
- Unsupervised
- Reinforcement

Supervised = Learning with a labeled training set

Unsupervised = Discover patterns in unlabeled data

Reinforcement = Learn to act based on feedback / reward

ML vs DL

ML ⇒ Input dataset → Feature extraction → Classification

↳ Small dataset is also acceptable

Feature extraction:
- ↳ Human dependant
- ↳ Difficult
- ↳ Human biasness

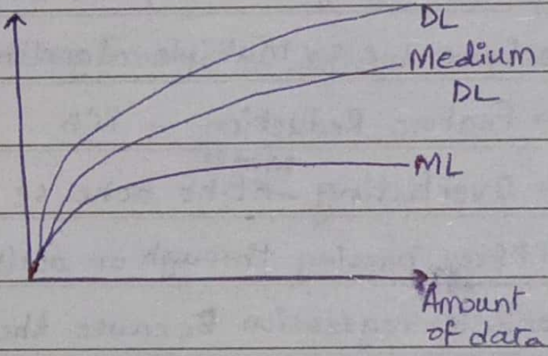
Classification:
- ↳ Depends on FE

DL (Merges FE and Classification) ⇒ Input data → Extracts Features + Classification
- Extracts Features: ↳ Not human dependant
- Classification: → Fine-tuned

↳ Through backpropogation, classification is fine-tuned which improves the accuracy

↳ Drawback requires a huge dataset because it needs to learn on its own.

↳ Why is it so hyped?
- → Processing Power has gotten cheap
- → Big Data
- → Algorithms advancement



→ The larger the data, the better the accuracy.

Why is DL useful?
- ↳ Learned features are easy to adapt, fast to learn
- ↳ Provides a very flexible, almost universal, learnable framework
- ↳ Manually designed features are often over-specified, incomplete and takes a long time to design and validate

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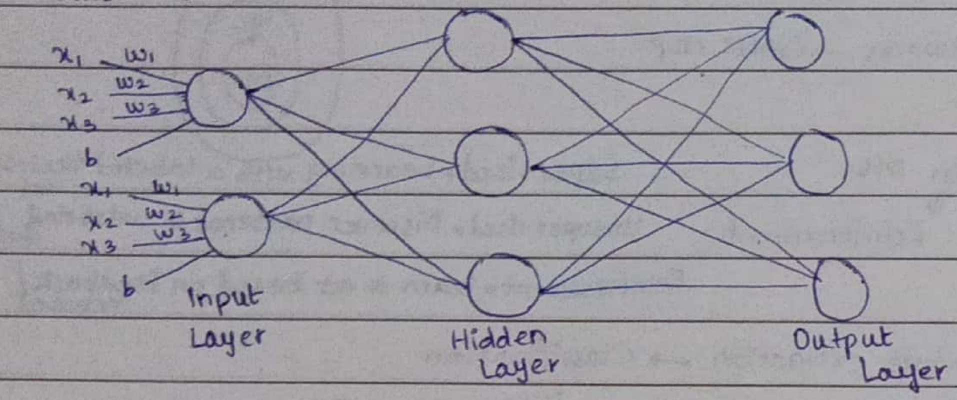
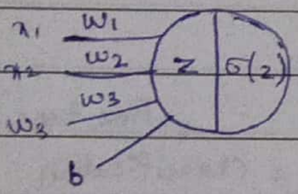
Neural Networks:



This is fully connected network but it is not always necessary.

W = weight

b = bias



$w_1x_1 + w_2x_2 + w_3x_3 + b$ → Output → Activation function

↓ simple linear regression equation

Activation function ↓
→ Adds non-linearity
→ Check krta hai kis value ko forward krna hai
→ Ek range mei laata hai

NN hidden layers <=2

DNN hidden Layers >2

→ Vanishing gradient problem in ML because of which got stuck.

→ Ensemble → Multiple algorithms ko le kr merge kr diya (bagging, boosting)

→ Feature Reduction → PCA

→ Overfitting → Model Bht ache se yaad kr leta hai features

→ After passing through an activation function, linear regression becomes logistic regression because the values are mapped from $(-\alpha, +\alpha)$ to either $(-1,1)$ or $(0,1)$ [RELU].

Forward Pass

1: $z = wx + b$

$a = g(z)$

2: $z = w^l a^{l-1} + b^l$

$a = g(z)$

Backward Pass (Derivative is taken)

1 = $\partial a = g(z)$

2. $\partial z = wa + b$

$\partial a = g(z)$

$$W^l = W^l - \alpha \, dW^l$$

↓ learning rate → kis bhaav se weights update horhe hain

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Parameters versus hyperparameters

Weights and bias — learning rate, number of iterations, number of layers, number of hidden units, choice of activation function

→ Parameters that control the weight parameters (hyperparameters)
↳ Should be fixed prior to training the NN

•> Model parameters are estimated from data during the training step

•> Model hyperparameters are manually set earlier and are used to assist estimation model parameter.

0 to 1 → Classification Algorithm (KNN, Naive Bayes) Linear = Continuous

Logistic Regression:- → Discrete

$z = \sum_{i=1}^{n} w_i x_i + b$ $h = \text{Sigmoid}(z)$ → Activation function

$\hookrightarrow \frac{1}{1+e^{-z}}$

Naive Bayes vs Logistic Regression

↳ Generative Classifier → Discriminative Classifier

↳ Learns more features and can regenerate it

↳ tries to find a unique feature to differentiate it.

$\sigma(z) = \frac{1}{1+e^{-z}} = z = -\alpha = \frac{1}{1+e^{\infty}} \sim 0$

$= \frac{1}{1+e^{-z}} = z = \alpha = \frac{1}{1+e^{-\infty}} \sim 1$

$x = [3, 2, 1, 3, 0, 4.19]$	$x = [2, 3, 5, 7, 1]$
$w = [2.5, -5, -1.2, 0.5, 2.0, 0.7]$	$w = [5, 6.1, 7.8, 2.3, 1]$
$b = 0.1$	$b = 0.2$
$\sum_{i=1}^{n=6} w_i x_i + b = 0.733$	$= 84.4$
$P(y=1 \mid x)$	
$P(y=0 \mid x) = 0.3$	

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$$P(y=1|x) = \frac{1}{1+e^{-z}}$$

$$P(y=0|x) = 1 - \frac{1}{1+e^{-z}} = \frac{1+e^{-z}-1}{1+e^{-z}} = \frac{e^{-z}}{1+e^{-z}}$$

$L(\hat{y}, y)$ — y: true value, $\hat{y}$: predicted value

Cross entropy, binary

$L_{CE} =$

$$P(y|x) = \hat{y}^{y}(1-\hat{y})^{1-y}$$

$$= \log\left(\hat{y}^{y}(1-\hat{y})^{1-y}\right)$$

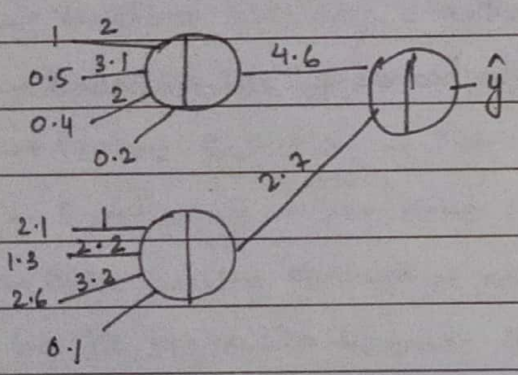
$$= \log \hat{y}^{y} + \log(1-\hat{y})^{1-y}$$

$$y \log \hat{y} + (1-y)\log(1-\hat{y}) \rightarrow \text{Log Likelihood}$$

$$y \log \sigma(z) + (1-y)\log(1-\sigma(z)) \qquad \sigma(z) = a$$

$$L_{CE} = y\log(a) + (1-y)\log a$$

Types of Logistic Regression
- Binary (2 classes)
- Multinomial (more than 2)
- Ordinal (More than 2 classes + order matters)



$y = 0.98$

1: $z_1 = 1(2) + 0.5(3.1) + 0.4(2) + 0.2 = 4.55$ $\qquad L_{CE} = -0.00102$

$a = 1/1+e^{-4.55} = 0.9895$

$z_2 = 2.1(1) + 1.3(2.2) + 2.6(3.2) + 0.1 = 13.38$

$a = 0.999998$

2:

$z_1 = 0.9895(4.6) + 0.999998(2.7) = 7.25$

$a = 0.99929$

$\hat{y} = 0.99929$

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$L_{CE}(\hat{y}, y) = -\log P(y|x)$

$-\left[y\log(\hat{y}) + (1-y)\log(1-\hat{y})\right]$ General Cross Entropy

Binary Cross Entropy (2 classes)

GRADIENT

$a(1-a).\,x_1$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial a} \cdot \frac{\partial a}{\partial z} \cdot \frac{\partial z}{\partial w_1}$$

$$\frac{\partial}{\partial a}\left[-y\log(a) - (1-y)\log(1-a)\right]$$

derivative of sigmoid $= a(1-a)$

$$\frac{-y}{a} - \frac{1(-1)}{1-a}(1-y) = \frac{-y}{a} + \frac{1-y}{1-a}$$

$z = w_1x_1 + w_2x_2 + b$

$a = \hat{y} = \sigma(z)$

$$\therefore \left[\frac{-y}{a} + \frac{1-y}{1-a}\right] \cdot a(1-a) \cdot x_1$$

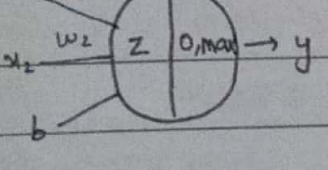
$$\frac{-y(1-a) + a(1-y)}{\cancel{a(1-a)}} \cdot \cancel{a(1-a)} \cdot x_1$$

$$(-y + \cancel{ay} + a - \cancel{ay}) \cdot x_1 = (a-y) \cdot x_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial a} \cdot \frac{\partial a}{\partial z} \cdot \frac{\partial z}{\partial w_2}$$

$$(a-y) \cdot x_2$$

$$\frac{\partial L}{\partial b} = a - y$$



AND Gate (0,0,-1)

OR Gate (1,1,0)

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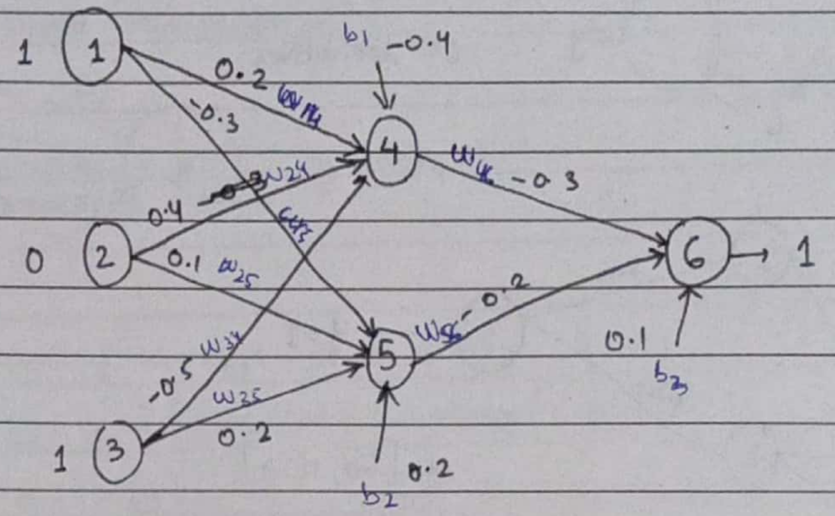

$\eta = 0.9$

$z_4 = -0.7$ $\qquad$ $z_5 = 0.1$

$a_4 = 0.332$ $\qquad$ $a_5 = 0.525$

$z_6 = \cancel{0.0546}$ -0.10403

$a_6 = \cancel{0.524}$ 0.4734

$L = \frac{1}{2}(\text{target} - \overset{\text{predicted}}{\text{output}})^2$ − MSE

$= \frac{1}{2}(1 - 0.474)^2 = 0.138$

$\frac{\partial L}{\partial w_{46}} = \frac{\partial L}{\partial a} \cdot \frac{\partial a}{\partial z} \cdot \frac{\partial z}{\partial w_{46}}$

$= (a - \text{target}) \cdot (a)(1-a) \cdot a_4$

$= (0.474 - 1)(0.474)(1 - 0.474) \cdot (0.332)$

$= -0.0435399$

$w_{46}^{new} = w_{46}^{old} - \eta \frac{\partial L}{\partial w_{46}}$

$= -0.2608 \approx -0.261$

$\frac{\partial L}{\partial w_{56}} = -0.068885$

$w_{56}^{new} = w_{56}^{old} - \eta \frac{\partial L}{\partial w_{56}}$

$\frac{\partial L}{\partial b_3} = -0.1311$

$= \cancel{-0.13499}$ $-0.138035 \simeq -0.138$

$b_3^{new} = b_3^{old} - \eta \frac{\partial L}{\partial b_3} = 0.21799 \simeq 0.218$

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$$\frac{\partial L}{\partial w_{14}} = \frac{\partial L}{\partial a_6} \cdot \frac{\partial a_6}{\partial z_6} \cdot \frac{\partial z_6}{\partial a_4} \cdot \frac{\partial a_4}{\partial z_4} \cdot \frac{\partial z_4}{\partial w_{14}}$$

$$= \frac{\partial L}{\partial b_3} \cdot \frac{\partial z_6}{\partial a_4} \cdot \frac{\partial a_4}{\partial z_4} \cdot \frac{\partial z_4}{\partial w_{14}}$$

$$= (a_6 - \text{target})(a_6)(1-a_6)(w_{46}) \cdot (a_4)(1-a_4)(x_1)$$

$$\frac{\partial L}{\partial w_{15}} = \frac{\partial L}{\partial a_6} \cdot \frac{\partial a_6}{\partial z_6} \cdot \frac{\partial z_6}{\partial a_5} \cdot \frac{\partial a_5}{\partial z_5} \cdot \frac{\partial z_5}{\partial w_{15}}$$

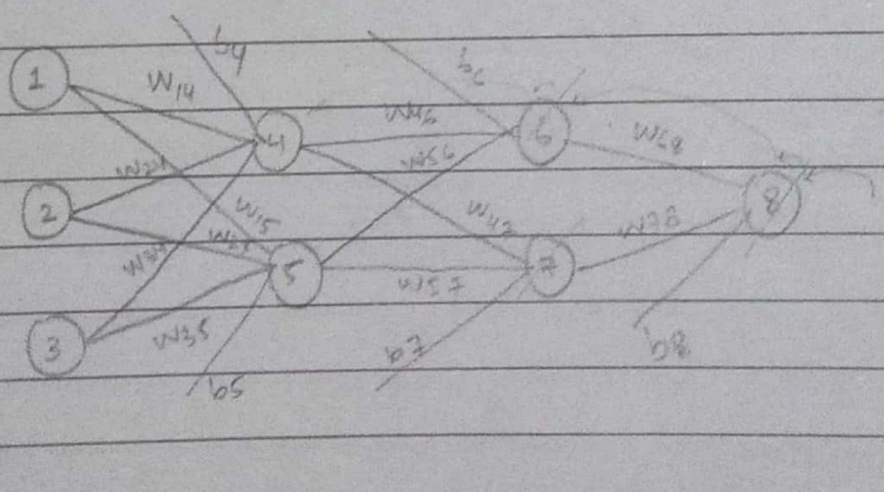
$$= (a_6 - \text{target})(a_6)(1-a_6)(w_{56}) \cdot (a_5)(1-a_5)(x_1)$$

$$\frac{\partial L}{\partial w_{24}} = (a_6 - \text{target})(a_6)(1-a_6)(w_{46})(a_4)(1-a_4)(x_2)$$

$$\frac{\partial L}{\partial w_{34}} = (a_6 - \text{target})(a_6)(1-a_6)(w_{46})(a_4)(1-a_4)(x_3)$$

$$\frac{\partial L}{\partial_{25}} = (a_6 - \text{target})(a_6)(1-a_6)(w_{56})(a_5)(1-a_5)(x_2)$$

$$\frac{\partial L}{\partial_{35}} = (a_6 - \text{target})(a_6)(1-a_6)(w_{56})(a_5)(1-a_5)(x_3)$$



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Sigmoid $= \frac{1}{1+e^{-z}}$

tanh $\cdot \frac{1-e^{-z}}{1+e^{-z}}$

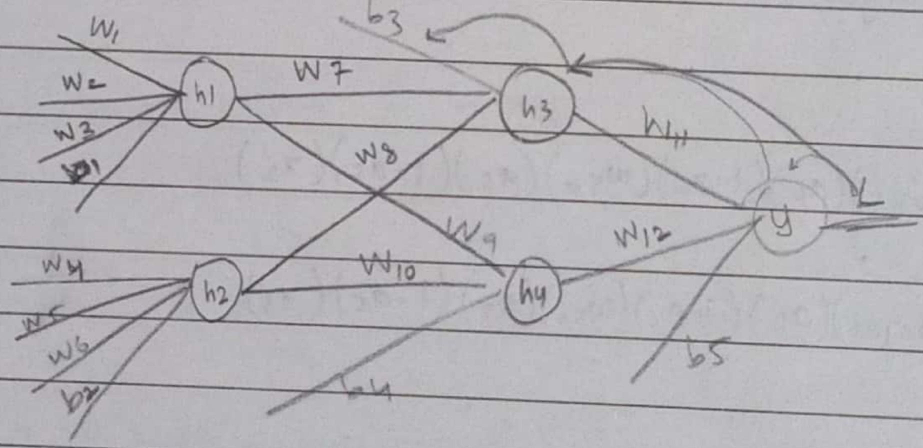
Relu $\max(0, z)$

Softmax $\frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$

$$\frac{\partial L}{\partial w_{14}} = \frac{\partial L}{\partial a_8} \cdot \frac{\partial a_8}{\partial z_8} \cdot \frac{\partial z_8}{\partial a_6} \cdot \frac{\partial a_6}{\partial z_6} \cdot \frac{\partial z_6}{\partial a_4} \cdot \frac{\partial a_4}{\partial z_4} \cdot \frac{\partial z_4}{\partial w_{14}}$$

$$L = \frac{1}{2}(y - a_8)^2$$

$$\frac{\partial L}{\partial w_{14}} = -(y-a_8) \cdot (a_8)(1-a_8) \cdot w_{68} \cdot (a_6)(1-a_6) \cdot w_{46} \cdot (a_4)(1-a_4) \cdot x_1$$



$$\frac{\partial L}{\partial h_3}$$

Code,
Regularization, ← DLP → Ruhal
Dropout

Adv, SMD → Isbah.

ICC → Both

FYP → Code → Ruhal

Paper → Isbah

Dance → Mahnoor

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Regularization

→ To avoid overfitting — training result good, testing result fail

→ Example L1, L2, Early stopping

Regularization (Prevent overfitting)

Optimization (Prevent underfitting) — training result bad

True Loss → Generalization error

Empirical Loss → Test error (val error)

L1: regularization coefficient

Cost = $(\text{loss}) + \lambda \sum_{i=1}^{n} \|w\| \quad \cancel{+ \sum_{i=1}^{n} \|w\|^2}$

L2

$+ \lambda \sum_{i=1}^{n} \|W\|^2$

Drop out / Gradient Descent

Scanned with CamScanner

Date

1 +

2 -

4 +

5 +

6 -

7 -

leaving '1' out

$S_p = \{4, 5\}$ $\mu_p = 4.5$

$S_n = \{2, 6, 7\}$ $\mu_n = 5$

1 + correct

leaving '2' out

$S_p = \{1, 4, 5\}$ $\mu_p = 3.33$

$S_n = \{6, 7\}$ $\mu_n = 6.5$

2 + wrong

leaving '4' out

$S_p = \{1, 5\}$ $\mu_p = 3$

$S_n = \{2, 6, 7\}$ $\mu_n = 5$

4 + correct

leaving '5' out

$S_p = \{1, 4\}$ $\mu_p = 2.5$

$S_n = \{2, 6, 7\}$ $\mu_n = 5$

5 - ~~correct~~ wrong

leaving '6' out

$S_p = \{1, 4, 5\}$ μ_p 3.33

$S_n = \{2, 7\}$ $\mu_n = 4.5$

6 - correct

leaving '7' out

$S_p = \{1, 4, 5\}$ $\mu_p = 3.33$

$S_n = \{2, 6\}$ $\mu_n = 4$

7 - correct

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CV

1

train

A	1	+
B	2	-
C	4	+
D	5	+

test

E	6	-
F	7	-

$S_p = \{1, 4, 5\}$ $\mu_p = 3.33$

$S_n = \{2\}$ $\mu_n = 2$

E = + wrong

F = + wrong

2

A	1	+
B	2	-
E	6	-
F	7	-
C	4	+
D	5	+

$S_p \{1\}$ $\mu_p = 1$

$S_n \{2, 6, 7\}$ $\mu_n = 5$

C = 4 - wrong

D = 5 - wrong

3

C	4	+
D	5	+
E	6	-
F	7	-
A	1	+
B	2	-

$S_p = \{4, 5\}$ 4.5

$S_n = \{6, 7\}$ 6.5

1 + correct

2 + wrong

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Regularization:-

→ A technique which makes slight modifications to the learning algorithm such that the model generalizes better.

→ To avoid overfitting

→ Penalizes the coefficients → In ML

→ Penalizes the weight matrices of the nodes → In DL

→ If regularization coefficient is so high that some of the weight matrices are nearly equal to zero → slight underfitting of the training data

→ Need to optimize the value of regularization coefficient

↳ Data Augmentation

↳ Early Stopping

↳ L1

↳ L2

L1 Regularization

→ Prevent overfitting of a model by adding a penalty term to the model's cost function,

Lasso $L1 = \lambda * \Sigma |w|$

$|w|$ → Model's weights or coefficients

λ → Regularization Strength (hyper parameter)

$\Sigma |w|$ → Represents the sum of absolute values of all weights

Higher λ → Reduce model's predictive power

lower λ → Increase the risk of overfitting

L2 Regularization

→ Prevent overfitting of a model by adding a penalty term to the model's cost function

Ridge ← $L2 = \lambda * \Sigma (w^2)$ → Sum of the squares of all weights

→ L2 differs from L1. L2 encourages the model's weights to be small and

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close to zero but doesnot necessarily set them exactly to zero, as L1 regularization does. L2 regularization is often used when all the features or variables are considered relevant, and a small weight is preferable to no weight for preventing overfitting.

DROPOUT

- NN overfits
- Optimal solution is to use a Bayesian framework. Infeasible when networks are big
- Dropout suggests that each unit should work with a random sample of other units.
- ChatGPT gave an example: "Think of it like a team of workers where some workers take time off during each workday. Each worker learns to do all the tasks necessary for the job, so if any one worker takes a day off, the team can still function effectively.
- At training (each iteration): Each unit is retained with a probability p.
- At test: The network is used as a whole. The weights are scaled down by a factor of p
- Dropout trains 2^n networks (n-number of units)

OR

- At training: Weights are scaled up by a factor of $1/p$
- At test: No scaling applied
  ↳ This method is used in TF.

$$r_i^{(l)} \sim \text{Bernoulli}(p)$$

$$\tilde{y}^{(l)} = r^{(l)} * y^{(l)}$$

$$z_i^{(l+1)} = w_i^{(l+1)} \tilde{y}^{(l)} + b_i^{(l+1)}$$

$$y_i^{(l+1)} = f\left(z_i^{(l+1)}\right)$$

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The effect of dropout on learned features:

- Without dropout, units tend to compensate for mistakes of other units
- This leads to overfitting, since the co-adaptations do not generalize to unseen data
- Dropout prevents co-adaptations by making the presence of other hidden units unreliable.

Weight Decay

- Limiting the growth of the weights in the network.

$$L_{new}(w) = L_{old}(w) + \frac{1}{2}\lambda \|w\|_2^2$$

→ Dropout has more advantages over weight decay.

- Dropout is scale-free
- Dropout is invariant to parameter scaling.

→ Dropout is a very good and fast regularization method.

→ Dropout is a bit slow to train (2-3 times slower than without dropout)

→