



# CIS 419/519 Recitation

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# Content

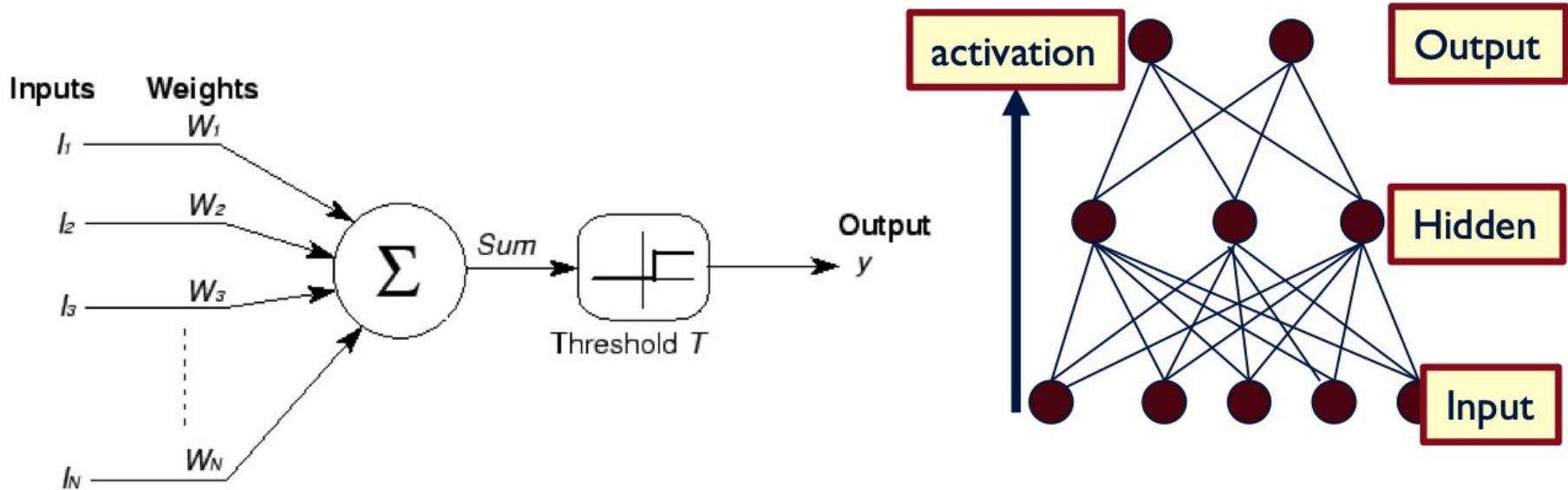
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- Neural Networks
- CNN
- Probability Review for Naive Bayes

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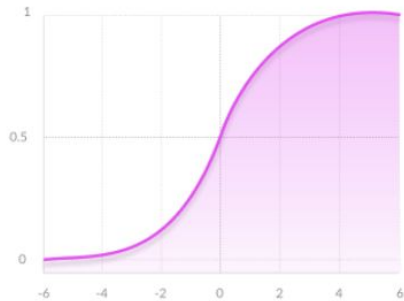
# Part I: Neural Network

# Basics about NN

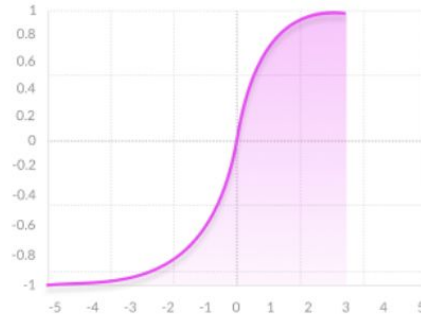


# Activation Function

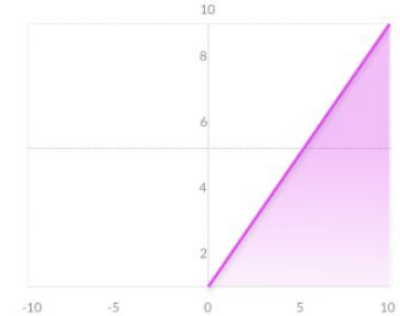
## Sigmoid / Logistic



## Tanh



## ReLU

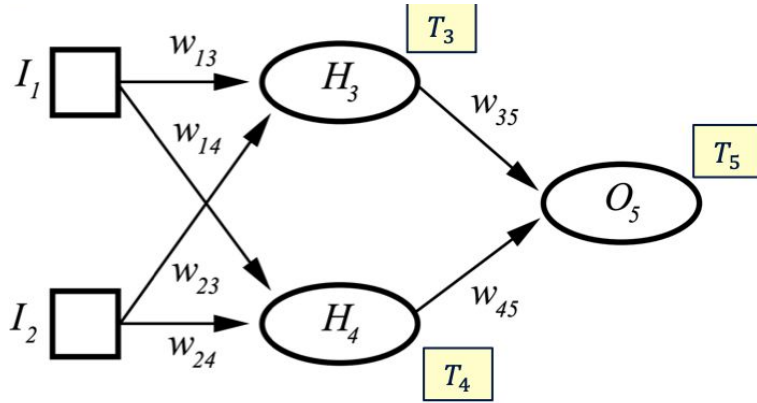


If you are working on CNN project, choosing a right activation function might be crucial

More to explore:

<https://missinglink.ai/guides/neural-network-concepts/7-types-neural-network-activation-functions-right/>

# Backpropagation



```
for i, data in enumerate(trainloader, 0):  
    # get the inputs; data is a list of [inputs, labels]  
    inputs, labels = data  
  
    # zero the parameter gradients  
    optimizer.zero_grad()  
  
    # forward + backward + optimize  
    outputs = net(inputs)  
    loss = criterion(outputs, labels)  
    loss.backward()  
    optimizer.step()
```

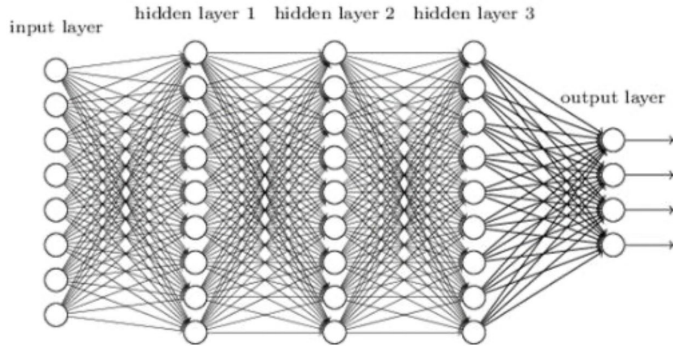
Tips for debugging:

- check gradient if you suspect nn is not really actively training

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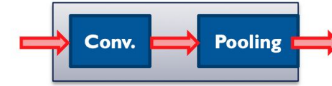
# Part 2: CNN

# MLP vs CNN

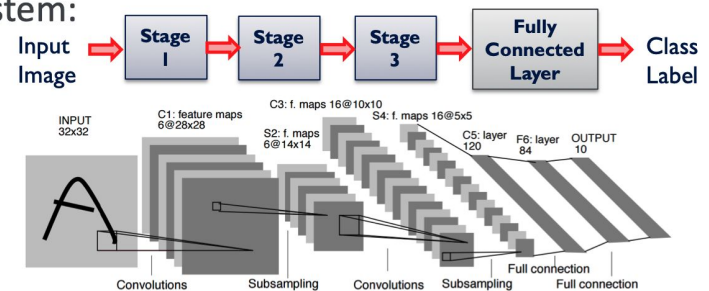


Useful in lot of fields such as:  
Reinforcement Learning or topics with relatively small feature space

- One stage structure:



- Whole system:



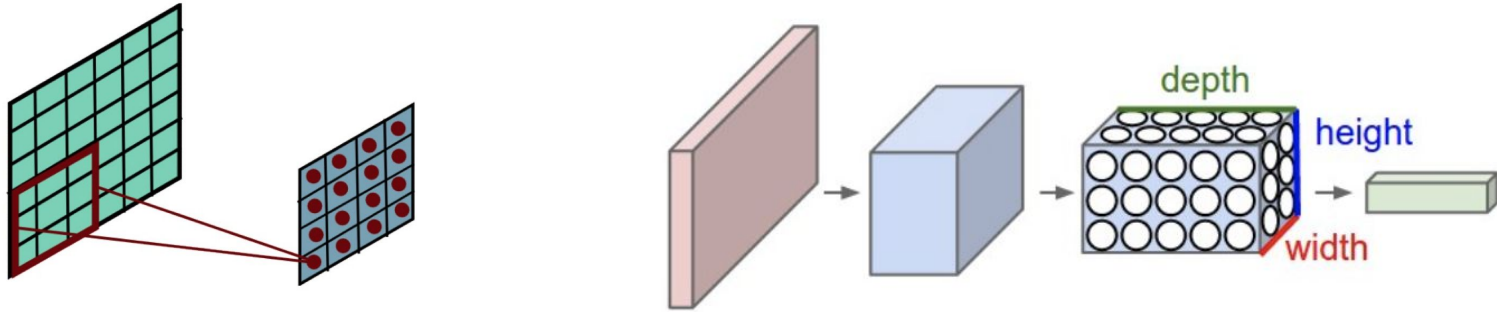
Deal with image/ Image Recognition or Image Generation:

large feature space (eg.  $1024 \times 1024 \times 3$ )



# Convolutional Operator

- objective: smartly shrink down feature sizes while maintain information



- Aggregate neighbor information
- Demo: <https://cs231n.github.io/convolutional-networks/>

# Be Careful with Channel

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

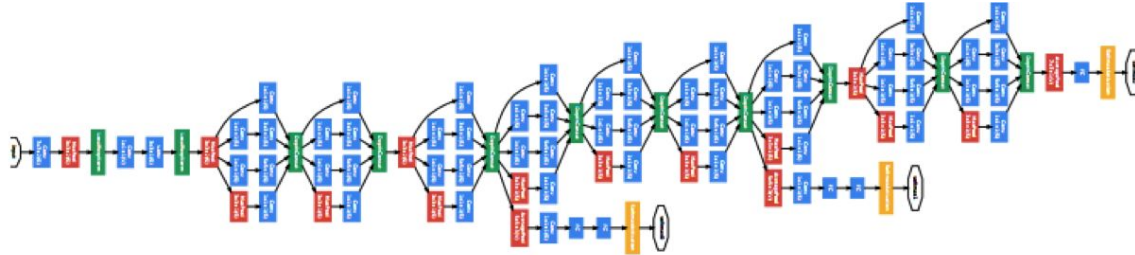
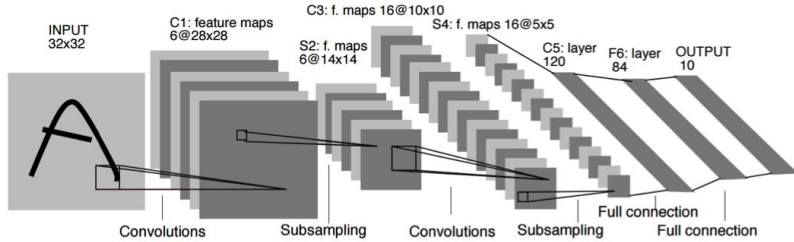
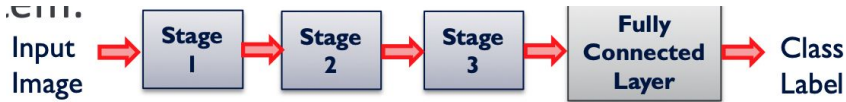
    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

## CONV2D

```
CLASS torch.nn.Conv2d(in_channels: int, out_channels: int, kernel_size: Union[T,
    Tuple[T, T]], stride: Union[T, Tuple[T, T]] = 1, padding: Union[T, Tuple[T,
    T]] = 0, dilation: Union[T, Tuple[T, T]] = 1, groups: int = 1, bias: bool =
    True, padding_mode: str = 'zeros')
```

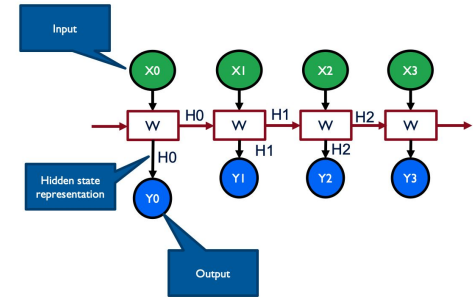
They need to match among layers

# Now Building the Network!



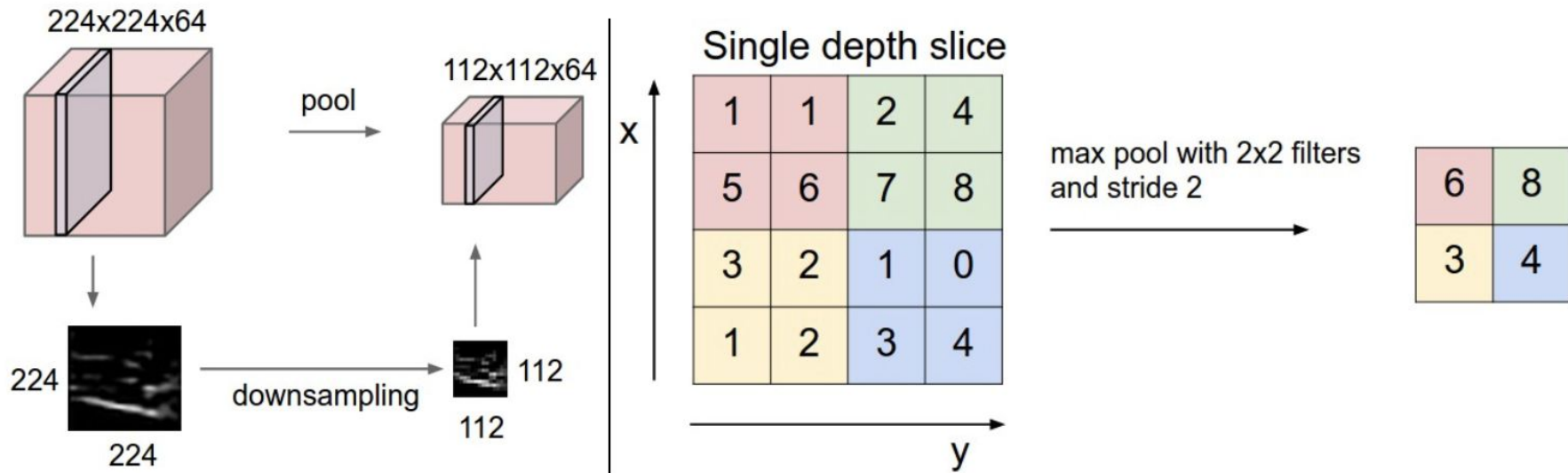
## Recurrent Neural Networks

- Infinite uses of finite structure



# Pooling

- Another trick to shrink down the image
- eg. Max Pooling - only remain the max one in a certain region



# Debug in Colab

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```
import pdb
```

[https://colab.research.google.com/drive/12jFFanVuZgm\\_wfrCFGBjVigPU2chqZD7?usp=sharing](https://colab.research.google.com/drive/12jFFanVuZgm_wfrCFGBjVigPU2chqZD7?usp=sharing)

# More Courses

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- ESE 546 Principles of Deep Learning (fall)
- CIS 680 Vision & Learning (fall)
- ESE 650 Learning In Robotics (spring) - modules about reinforcement learning
- CIS 522 - Deep Learning for Data Science(spring)

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# Part 2: Probability for Naive Bayes

# Random Variables

Suppose Dan tosses a fair coin 6 times. Examples of random variables (r.v.):

- Let  $X$  be the number of tails.
- Let  $Y$  be the number of heads.
- Let  $W$  be the number of tails in the first 3 throws.
- Let  $T$  be the number of tosses until first head.
- Let  $V$  denote whether or not the fifth toss is a head.
- Let  $U$  be the number of consecutive tail-head tosses.
- ~~$M$~~  Let  $M$  be the probability that the first toss is a head.

R.V.'s are numerical descriptions of an **outcome** of a statistical experiment.



# Probability & Events

An event is a **set of outcomes** of a statistical experiment. The probability of an event is the chance that the outcome of a trial belongs (or ‘lands’ on) to the set of outcomes that is the event, i.e. ( $\#$  of outcomes in event / Total  $\#$  of outcomes)

Number of heads (x)	0	1	2	3	4	5	6
P(X=x)	P(X=0)	P(X=1)	P(X=2)	P(X=3)	P(X=4)	P(X=5)	P(X=6)

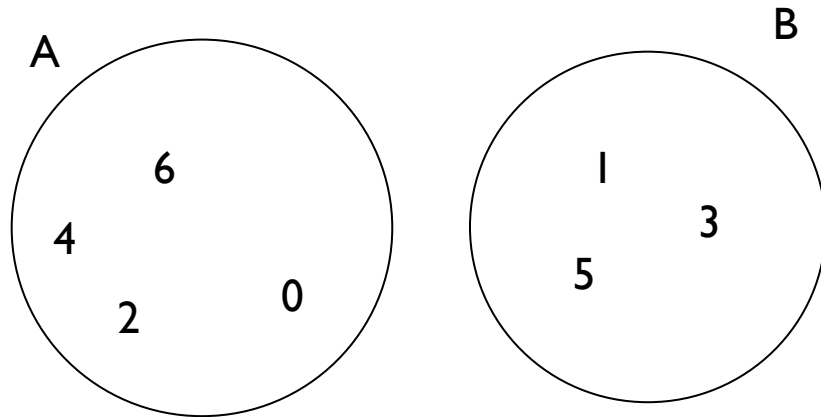
Example: Let  $X$  denote the number of heads that Dan tossed. Find  $P(X \text{ is even})$ .

The event “ $X$  is even” is the set of values of  $X = \{0, 2, 4, 6\}$ .

$$P(X \text{ is even}) = P(X=0) + P(X=2) + P(X=4) + P(X=6)$$

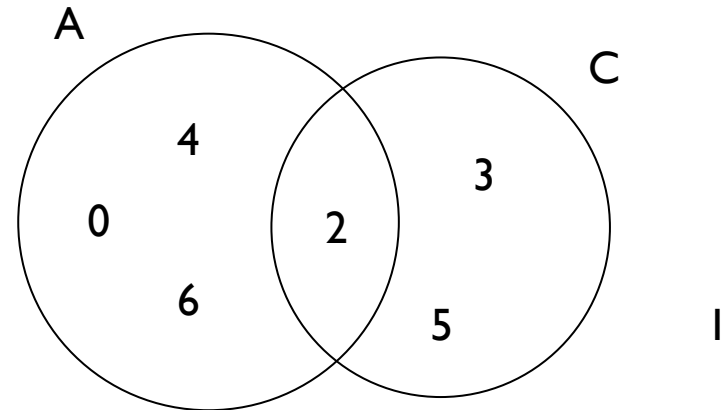
# Combining Events: Exclusivity

## Mutually-exclusive events



where A is the event where Dan tossed an even number of heads and B odd.

## Not exclusive events



where A is the event where Dan tossed an even number of heads and C prime.

# Combining Events: Independence

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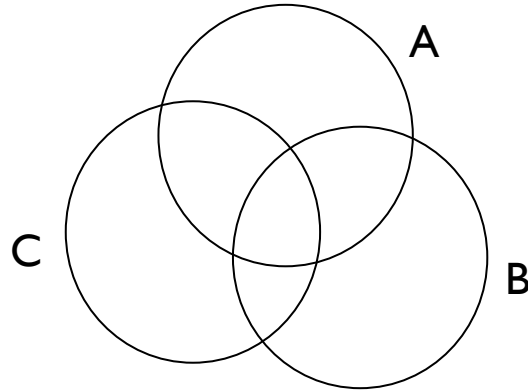
Two events A and B are independent iff the following formula applies:

$$P(A \cap B) = P(A) \cdot P(B)$$

The probability of A occurring **should not** be affected by the occurrence of event B and vice versa.

# Principle of Inclusion - Exclusion (PIE)

Let's take a look at an example between events A, B and C:



$$\begin{aligned} |A \cup B \cup C| &= |A| + |B| + |C| \\ &\quad - |A \cap B| - |A \cap C| - |B \cap C| \\ &\quad + |A \cap B \cap C| \end{aligned}$$

# Expectation

Going back to our example of Dan tossing a fair coin 6 times,...

Number of heads (x)	0	1	2	3	4	5	6
$P(X=x)$	$P(X=0)$	$P(X=1)$	$P(X=2)$	$P(X=3)$	$P(X=4)$	$P(X=5)$	$P(X=6)$
$x \cdot P(X=x)$	0	$P(X=1)$	$2 \cdot P(X=2)$	$3 \cdot P(X=3)$	$4 \cdot P(X=4)$	$5 \cdot P(X=5)$	$6 \cdot P(X=6)$

$$E(X) = \sum_{x=0}^6 x \cdot P(X = x)$$

Expectation of a r.v.  $X$  is the **weighted average** of the possible values that  $X$  can take, each value being weighted according to the probability of that event occurring.

# Variance

Going back to our example of Dan tossing a fair coin 6 times,...

Number of heads (x)	0	1	2	3	4	5	6
P(X=x)	P(X=0)	P(X=1)	P(X=2)	P(X=3)	P(X=4)	P(X=5)	P(X=6)
x•P(X=x)	0	P(X=1)	2•P(X=2)	3•P(X=3)	4•P(X=4)	5•P(X=5)	6•P(X=6)
x <sup>2</sup> •P(X=x)	0	P(X=1)	4•P(X=2)	9•P(X=3)	16•P(X=4)	25•P(X=5)	36•P(X=6)

$$\text{Var}(X) = \sum_{x=0}^6 x^2 \cdot P(X = x) - (E(X))^2$$

Variance of a r.v.  $X$ , informally, measures how far a set of numbers is **spread out from their average value**.

# Variance

Going back to our example of Dan tossing a fair coin 6 times,...

Number of heads (x)	0	1	2	3	4	5	6
P(X=x)	P(X=0)	P(X=1)	P(X=2)	P(X=3)	P(X=4)	P(X=5)	P(X=6)
x•P(X=x)	0	P(X=1)	2•P(X=2)	3•P(X=3)	4•P(X=4)	5•P(X=5)	6•P(X=6)
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# Conditional Probability

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We denote the probability of an event A occurring, given another event B occurring with the following notation:

$$P(A | B)$$

We assume / know that event B is has occurred / is occurring. And with this assumption, we aim to find the probability A occurring. So, if 2 events A and B are independent,

$$P(A | B) = P(A); P(B | A) = P(B)$$

because the given occurrence does not affect the probability of the event of interest occurring.