



Probability Basics

Computer Vision

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Random Variable

What is it?

Is it 'random'?

Is it a 'variable'?

Random Variable

What is it?

Is it 'random'?

not in the traditional sense

Is it a 'variable'?

not in the traditional sense

Random Variable:

a variable whose possible values are numerical outcomes of a random phenomenon

<http://www.stat.yale.edu/Courses/1997-98/101/ranvar.htm>

Random variable:

a measurable function from a probability space into a measurable space known as the state space (Doob 1996)

<http://mathworld.wolfram.com/RandomVariable.html>

Random variable:

a function that associates a unique numerical value with every outcome of an experiment

http://www.stats.gla.ac.uk/steps/glossary/probability_distributions.html



outcome
(face of a penny) $\xrightarrow{\text{random variable}}$ value
(heads or tails)



0: heads

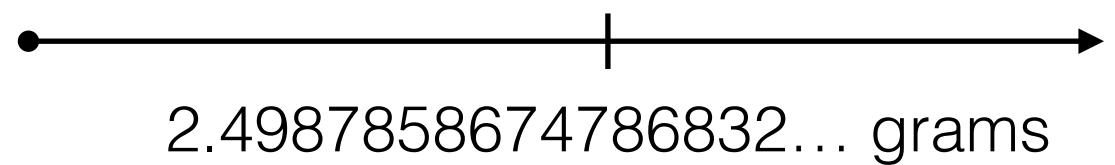


1: tails

What kind of random variable is this?



Discrete.
Can enumerate all possible outcomes



outcome
(mass of a penny)

random variable

value
(a number)



2.4987858674786832... grams

What kind of random variable is this?

outcome
(mass of a penny)

random variable

value
(a number)



2.4987858674786832... grams

Continuous.
Cannot enumerate all possible outcomes

Random Variables are typically denoted with a capital letter

X, Y, A, \dots

Values of an RV are typically denoted with lower case

$X = x$ x

“RV is equal to a certain value”

or just the value
(many times this is also used to mean the RV!
You'll have to figure it out from the context)

Probability:

the chance that a particular event (or set of events) will occur expressed on a linear scale from 0 (impossibility) to 1 (certainty)

<http://mathworld.wolfram.com/Probability.html>



0: heads

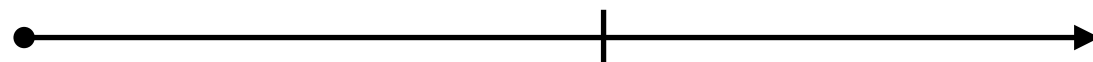
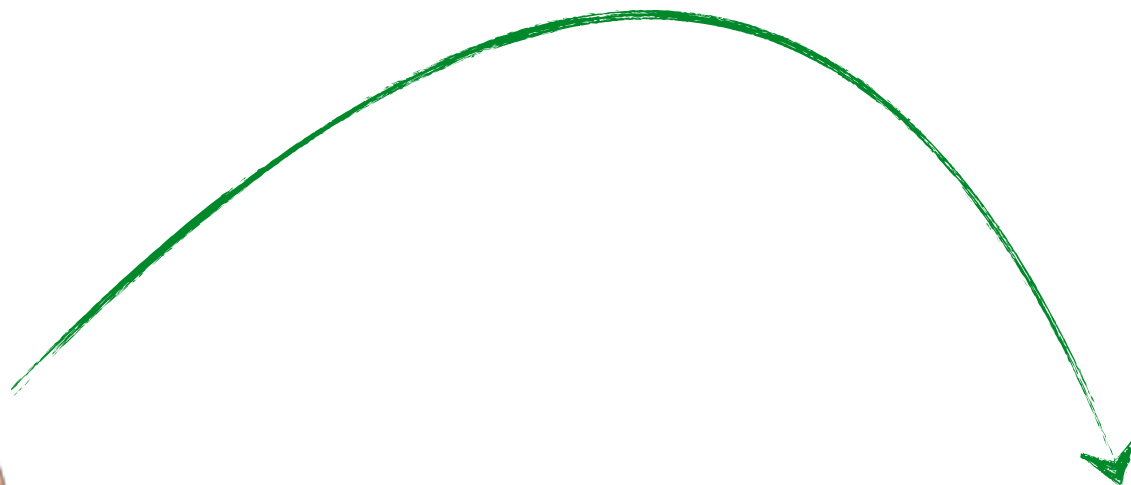


1: tails

$$p(X = 0) = 0.5$$

$$p(X = 1) = 0.5$$

$$p(X = 0) + p(X = 1) = 1.0$$



2.4987858674786832... grams

$$\int p(x) dx = 1$$

Probability Axioms:

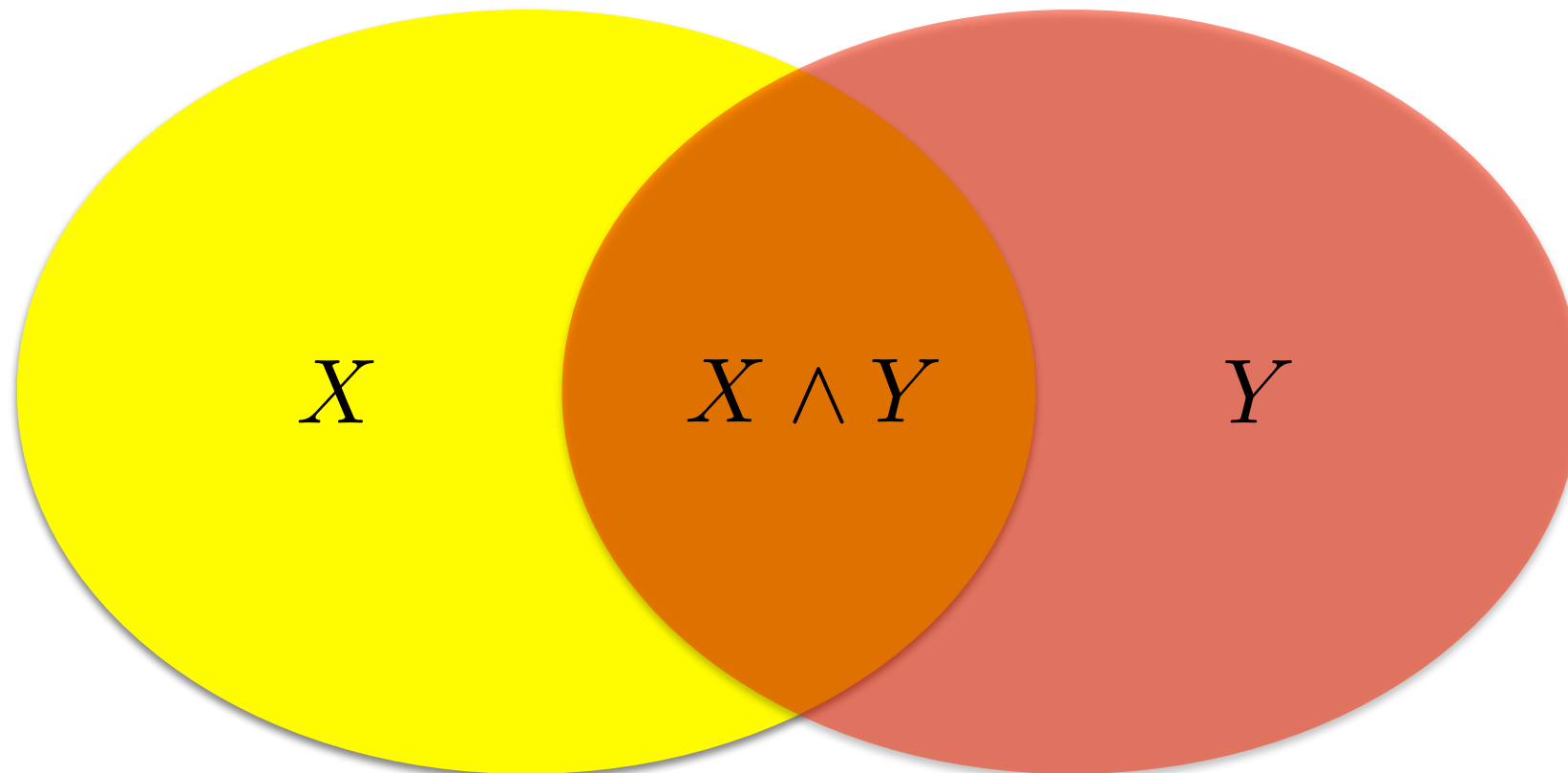
$$0 \leq p(x) \leq 1$$

$$p(\text{true}) = 1$$

$$p(\text{false}) = 0$$

$$p(X \vee Y) = p(X) + p(Y) - P(X \wedge Y)$$

$$p(X \vee Y) = p(X) + p(Y) - P(X \wedge Y)$$



Joint Probability

$$p(x, y)$$

When random variables are **independent**
(a sequence of coin tosses)

$$p(x, y) = p(x)p(y)$$

When random variables are **dependent**

$$p(x, y) = p(x|y)p(y)$$



this is a conditional probability defined next ...

Conditional Probability

$$p(x|y)$$

Conditional probability of x given y

$p(x|y)$ is the short hand for ?

in terms of the random variables **X** and **Y**

Conditional Probability

$$p(x|y)$$

Conditional probability of x given y

$p(x|y)$ is the short hand for $p(X = x|Y = y)$

How is it related to the joint probability?

$$p(x|y) = \frac{p(x, y)}{?}$$

Conditional Probability

$$p(x|y)$$

Conditional probability of x given y

$p(x|y)$ is the short hand for $p(X = x|Y = y)$

$$p(x|y) = \frac{p(x, y)}{p(y)}$$

Conditional probability is the probability of the union of the events x and y divided by the probability of event y

Bayes' Rule

$$\underset{\text{posterior}}{p(x|y)} = \frac{\overset{\text{likelihood}}{p(y|x)} \text{ ?}}{\text{?}}$$

What's the relationship between the posterior and the likelihood?

Bayes' Rule

$$\underset{\text{posterior}}{p(x|y)} = \frac{\overset{\text{likelihood}}{p(y|x)} \overset{\text{prior}}{p(x)}}{\underset{\text{evidence (observation prior)}}{p(y)}}$$

How do you compute the evidence (observation prior)?

Bayes' Rule

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)}$$

posterior likelihood prior
evidence (observation prior)

How do you compute the evidence (observation prior)?

$$p(x|y) = \frac{p(y|x)p(x)}{\sum_{x'} p(y|x')p(x')}$$

evidence (expanded)

Bayes' Rule

$$\underset{\text{posterior}}{p(x|y)} = \frac{\overset{\text{likelihood}}{p(y|x)} \overset{\text{prior}}{p(x)}}{\underset{\text{evidence}}{p(y)}}$$

Evidence (observation prior) is also called the
normalization factor


$$p(x|y) = \eta p(y|x)p(x)$$

$$p(x|y) = \frac{1}{Z} p(y|x)p(x)$$

Bayes' Rule with 'evidence'

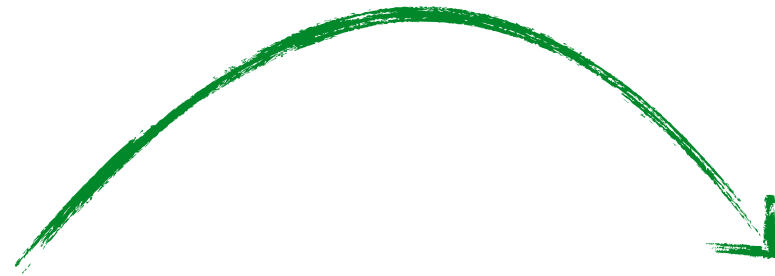
$$p(x|y, e) = \frac{p(y|x, e)p(x|e)}{p(y|e)}$$

Marginalization


$$p(x) = \sum_y p(x, y)$$

Marginalize out y

Conditioning




$$p(x) = \sum_y p(x|y)p(y)$$

Conditioned on y

Example: A visit to the Dentist

- **Toothache:** boolean variable indicating whether the patient has a toothache
- **Cavity:** boolean variable indicating whether the patient has a cavity
- **Catch:** whether the dentist's probe catches in the cavity



	<i>toothache</i>		\neg <i>toothache</i>	
	<i>catch</i>	\neg <i>catch</i>	<i>catch</i>	\neg <i>catch</i>
<i>cavity</i>	.108	.012	.072	.008
\neg <i>cavity</i>	.016	.064	.144	.576

A table of joint probabilities

Joint probability over three (dependent) variables

	<i>toothache</i>		\neg <i>toothache</i>	
	<i>catch</i>	\neg <i>catch</i>	<i>catch</i>	\neg <i>catch</i>
<i>cavity</i>	.108	.012	.072	.008
\neg <i>cavity</i>	.016	.064	.144	.576

$$p(\textit{cavity}) = ?$$

Recall: $p(x) = \sum_y p(x, y)$ Marginalization

Joint probability over three (dependent) variables

	<i>toothache</i>		\neg <i>toothache</i>	
	<i>catch</i>	\neg <i>catch</i>	<i>catch</i>	\neg <i>catch</i>
<i>cavity</i>	.108	.012	.072	.008
\neg <i>cavity</i>	.016	.064	.144	.576

$$p(cavity) = ?$$

$$p(cavity) = 0.108 + 0.012 + 0.072 + 0.008 = 0.2$$

Joint probability over three (dependent) variables

	<i>toothache</i>		\neg <i>toothache</i>	
	<i>catch</i>	\neg <i>catch</i>	<i>catch</i>	\neg <i>catch</i>
<i>cavity</i>	.108	.012	.072	.008
\neg <i>cavity</i>	.016	.064	.144	.576

$$p(cavity|toothache) = ?$$

Joint probability over three (dependent) variables

	<i>toothache</i>		\neg <i>toothache</i>	
	<i>catch</i>	\neg <i>catch</i>	<i>catch</i>	\neg <i>catch</i>
<i>cavity</i>	.108	.012	.072	.008
\neg <i>cavity</i>	.016	.064	.144	.576

$$\begin{aligned}
 p(\text{cavity}|\text{toothache}) &= \frac{p(\text{cavity}, \text{toothache})}{p(\text{toothache})} \\
 &= \frac{0.108 + 0.012}{0.108 + 0.012 + 0.016 + 0.064} \\
 &= 0.6
 \end{aligned}$$