

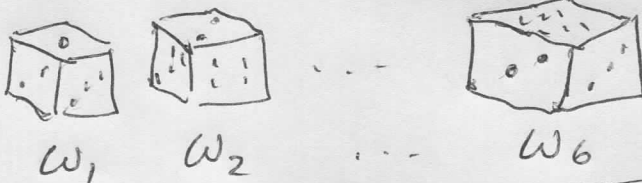
Probability

Sample space: all possible worlds

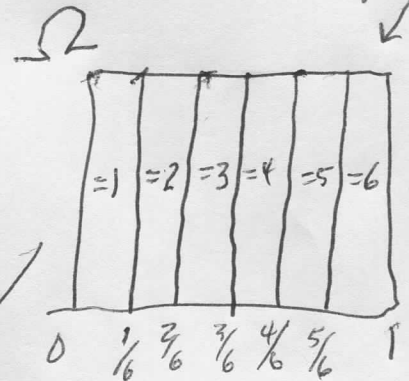
- mutually exclusive
- exhaustive

} called Ω

e.g., the rolls of a die



Why rectangular?



Probability model: associates a probability to each world

e.g., $p(w_i) = \frac{1}{6}$

areas are equal
means prob. = $\frac{1}{6}$

$$0 \leq \text{Prob}(w) \leq 1 \quad \forall w \in \Omega$$

$$\sum_{w \in \Omega} \text{Prob}(w) = 1$$

events: characterized by a set of worlds which make event true

characterized as a proposition ϕ

e.g., consider 2 dice

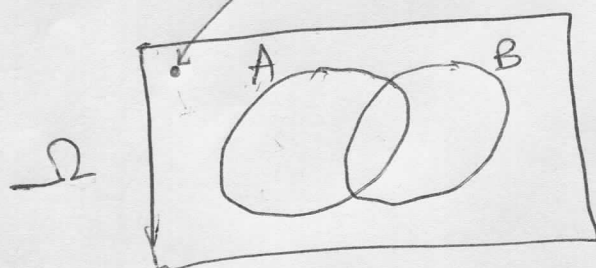
and $\phi \equiv$ sum of dice is 7

$$\text{then } \text{Prob}(\phi) = \sum_{\substack{w_i \text{ makes } \phi \text{ true} \\ \text{worlds where } \phi \text{ is true}}} \text{Prob}(w_i) = \sum [P(1,6) + P(2,5) + P(3,4) + P(4,3) + P(5,2) + P(6,1)] = \frac{1}{6}$$

Consider as a Sample Space diagram

E.g., 2 variables: $A \equiv$ I stay home
 $B \equiv$ It's raining

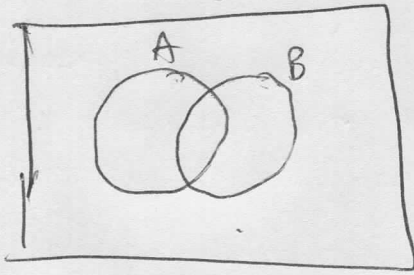
How to draw? what is a sample?



Usually
 where $P(B) \propto \text{area}(B)$
 $P(A) \propto \text{area}(A)$

what is a world? Both A and B are
 a function of time!

Usual diagram



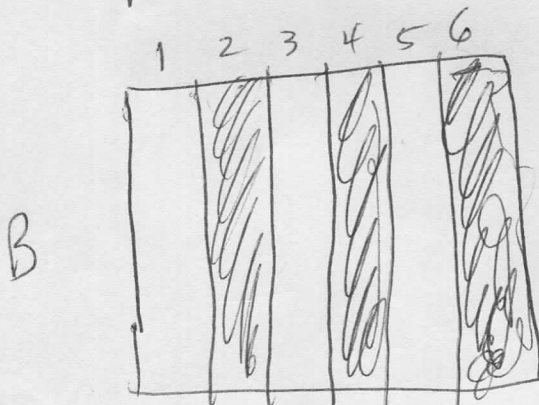
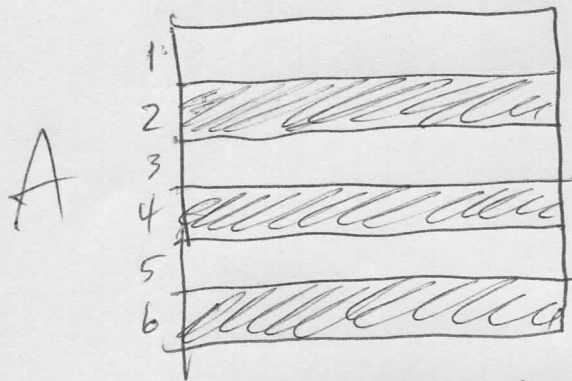
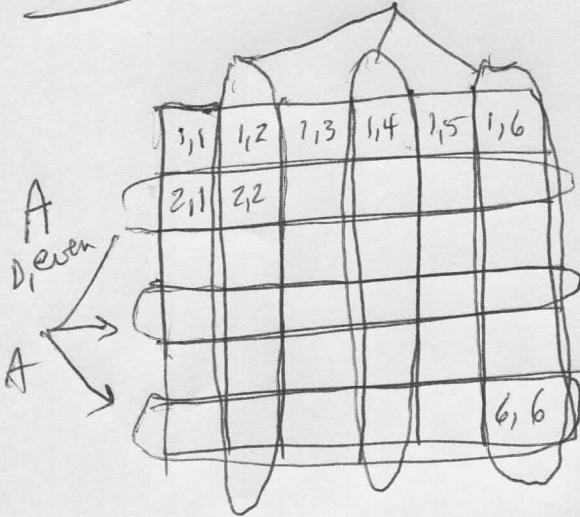
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Consider all logical combinations

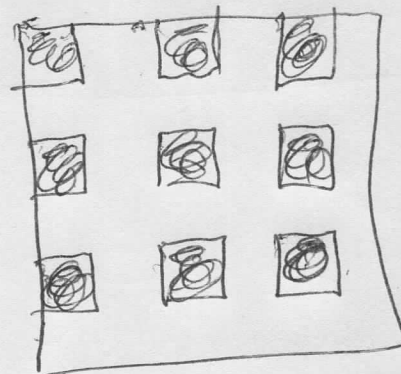
A	B
0	0
0	1
1	0
1	1

Try:

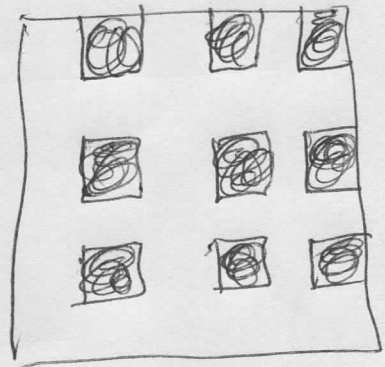
B even



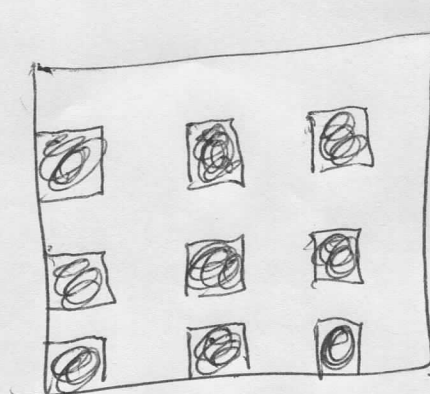
$\neg A \& \neg B$



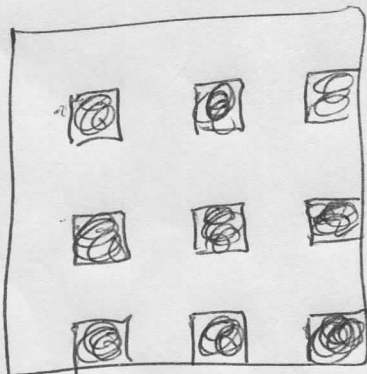
$\neg A \& B$



$A \& \neg B$



$A \& B$



Turns out:

$$P(\neg A \& \neg B)$$

$$P(\neg A \& B)$$

$$P(A \& \neg B)$$

$$P(A \& B)$$

these probabilities provide the
full joint probability
distribution and

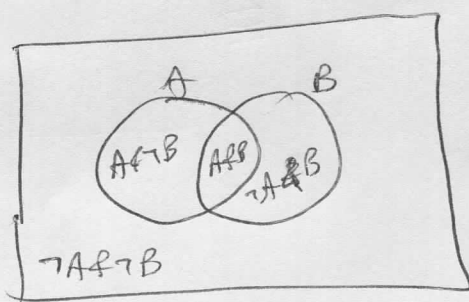
any event's probability can be computed from these.

E.g., $P(A \text{ even}) = P(A \& \neg B) + P(A \& B)$

if $P(\neg A \& \neg B) = P(\neg A \& B) = P(A \& \neg B) = P(A \& B) = 1/4$

then $P(A \text{ even}) = 1/4 + 1/4 = 1/2$

May be easier to think about as:



e.g., $P(A \vee B)$

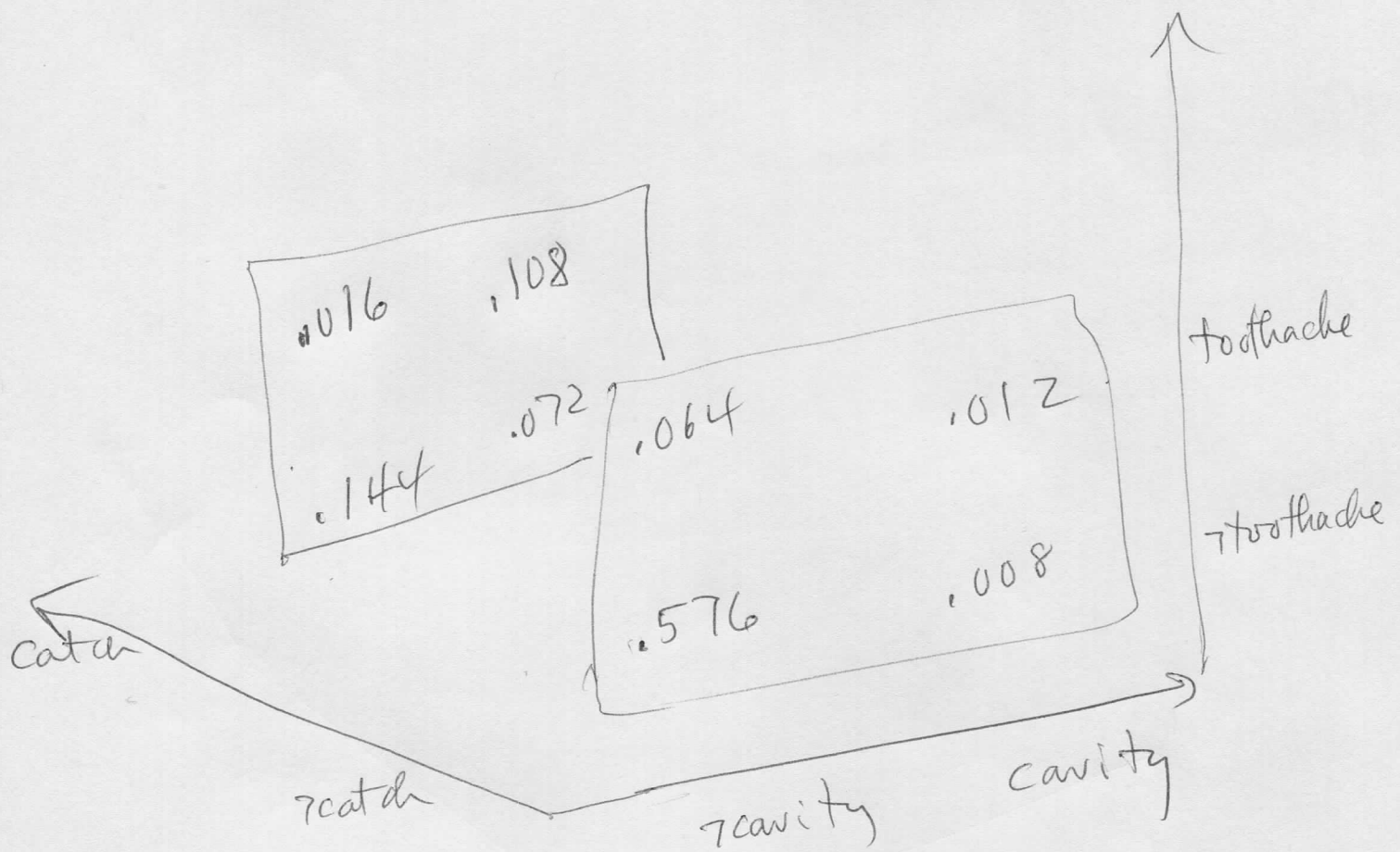
$$= P(A \& \neg B) + P(\neg A \& B) + P(A \& B)$$

all inside the 2
circles

also called complete conjunction set

Consider a full joint probability distribution
for 3 variables

13/4a



e.g., $P(\neg \text{cavity} \& \neg \text{catch} \& \neg \text{toothache}) = .576$

$$P(\text{cavity}) = .008 + .012 + .072 + .108 = 0.2$$

called marginalization or marginal probability

add up over all complete conjunctions
that make proposition true

Then can find:

$$\begin{aligned} P(A) &= P(A \& \neg B) + P(A \& B) \\ P(B) &= P(\neg A \& B) + P(A \& B) \end{aligned} \quad \left. \vphantom{\begin{aligned} P(A) &= P(A \& \neg B) + P(A \& B) \\ P(B) &= P(\neg A \& B) + P(A \& B) \end{aligned}} \right\} \text{ know these}$$

$$P(A \cup B) = P(A) + P(B) - P(A \& B) \quad \text{why}$$

because $\downarrow$

$$P(A \& \neg B) + \underline{P(A \& B)} + P(\neg A \& B) + \underline{P(A \& B)}$$

but $P(A \cup B) = P(A \& \neg B) + P(\neg A \& B) + P(A \& B)$

$\rightarrow$ since there's one $P(A \& B)$ too many $\therefore$ subtract one

Probabilities so far are unconditional or prior

But we want to use visual features to classify!

How to use evidence?

$P(\text{class} \mid \text{features}) \equiv \text{prob. of class given features}$

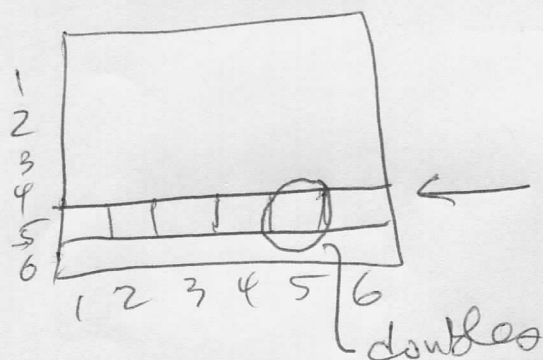
Defined as:

$$P(A \mid B) = \frac{P(A \& B)}{P(B)}$$

13/6

E.g.,

$$P(\text{doubles} \mid \text{Die}_1 = 5) = \frac{P(\text{doubles} \wedge \text{Die}_1 = 5)}{P(\text{Die}_1 = 5)}$$
$$= \frac{\frac{1}{36}}{\frac{1}{6}} = \frac{1}{6}$$



Die₁ = 5 Given this,
only 1 in 6 chance
of doubles

can re-write as

$$P(A|B)P(B) = P(A \& B)$$

Also $P(B|A)P(A) = P(A \& B)$

} product rule

$$\Rightarrow P(B|A) = \frac{P(A|B)P(B)}{P(A)} \quad \text{Bayes' rule}$$

For us

$$P(\text{class} | \text{features}) = \frac{P(\text{features} | \text{class}) P(\text{class})}{P(\text{features})}$$

Consider Euler number

A : 16/17 have Euler # = 0

$$P(A | \text{Euler} = 0) = \frac{P(\text{Euler} = 0 | A) P(A)}{P(\text{Euler} = 0)}$$

$$= \frac{16}{17} \cdot 0.0227$$

?

→ How can we find this?

e : 67/67 have Euler # = 0

$$P(e | \text{Euler} = 0) = \frac{P(\text{Euler} = 0 | e) P(e)}{P(\text{Euler} = 0)}$$

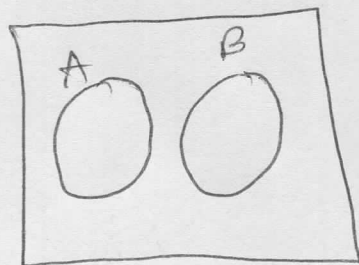
$$= \frac{1 \cdot 0.0895}{P(\text{Euler} = 0)}$$

So, given only Euler #, then

~~P(e)~~ e is more probable

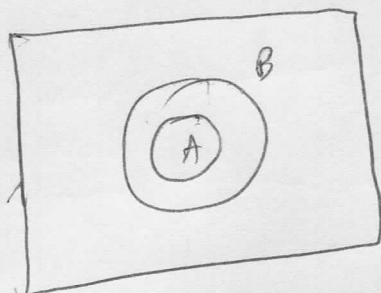
Given $A + B$, what does it mean for them to be independent?

Case 1



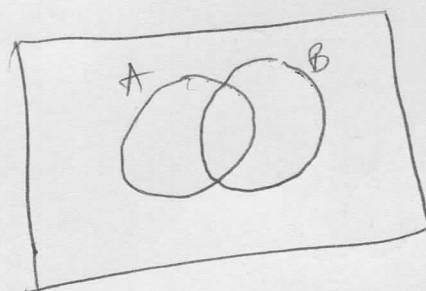
? $P(A) = \frac{1}{4}$
 $P(B) = \frac{1}{4}$

Case 2



? $P(B) = \frac{1}{4}$
 $P(A) = \frac{1}{8}$

Case 3



? $P(A) = \frac{1}{4}$
 $P(B) = \frac{1}{4}$
 $P(A \& B) = \frac{1}{16}$

Rule is $A + B$ are independent (pairwise) if:

$$P(A|B) = P(A) \quad \text{and} \quad P(B|A) = P(B)$$

$$\Rightarrow P(A \& B) = P(A|B)P(B) = P(A)P(B)$$

Case 1 ? if B is true, then $P(A) = 0$. $\times$

Case 2 ? if B is true, then $P(A|B) = \frac{P(A \& B)}{P(B)} = \frac{P(A)}{P(B)} \times$

Case 3 ? if B is true, then $P(A|B) = \frac{P(A \& B)}{P(B)} = \frac{1/16}{1/4} = \frac{1}{4} = P(A)$

Observation Mutual independence is

when all combinations of n variables satisfy:

$$P(A_1 \& A_2 \& \dots \& A_k) = P(A_1)P(A_2)\dots P(A_k)$$

pairwise independence does NOT imply
mutual independence

$$P(A) = P(B) = \frac{1}{2} \quad P(C) = \frac{1}{4}$$

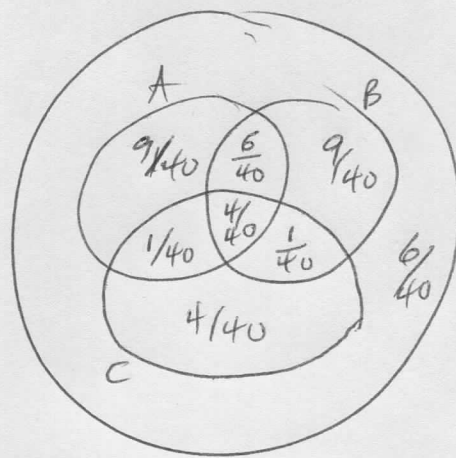
$$P(A|B) = P(A|C) = \frac{1}{2} = P(A)$$

$$P(B|A) = P(B|C) = \frac{1}{2} = P(B)$$

$$P(C|A) = P(C|B) = \frac{1}{4} = P(C)$$

$$P(A|BC) = \frac{\frac{4}{40}}{\frac{5}{40}} = \frac{4}{5} \neq \frac{1}{2}$$

$$= \frac{P(A \& B \& C)}{P(B \& C)}$$



Back to Bayes classification

let $\vec{x} = (x_1, x_2, \dots, x_n)$ be feature vector

then assigns probabilities to m classes:

$$P(C_k | \underbrace{x_1, x_2, \dots, x_n}_{x_1 \& x_2 \& \dots \& x_n})$$

Then:

$$P(C_k | \vec{x}) = \frac{P(\vec{x} | C_k) P(C_k)}{P(\vec{x})} \quad k=1:m$$

$$P(C_k, x_1, x_2, \dots, x_n) = P(x_1, x_2, \dots, x_n, C_k)$$

$$= P(x_1 | x_2, x_3, \dots, x_n, C_k) P(x_2, x_3, \dots, x_n, C_k)$$

$$= P(x_1 | x_2, x_3, \dots, x_n, C_k) P(x_2 | x_3, x_4, \dots, x_n, C_k) P(x_3, \dots, x_n, C_k)$$

$$\vdots$$

$$= P(x_1 | x_2, x_3, \dots, x_n, C_k) P(x_2 | x_3, x_4, \dots, x_n, C_k) \dots P(x_{n-1} | x_n, C_k) P(x_n | C_k) P(C_k)$$

assume x_i are mutually independent (Euler^{C.S.} #, height)

$$\text{then } P(x_i | x_{i+1}, \dots, x_n, C_k) = P(x_i | C_k)$$

$$\text{and } P(C_k | x_1, x_2, \dots, x_n, C_k) \propto P(C_k, x_1, \dots, x_n)$$

$$= P(C_k) P(x_1 | C_k) \dots P(x_n | C_k)$$

$$= P(C_k) \prod_{i=1}^n P(x_i | C_k)$$