

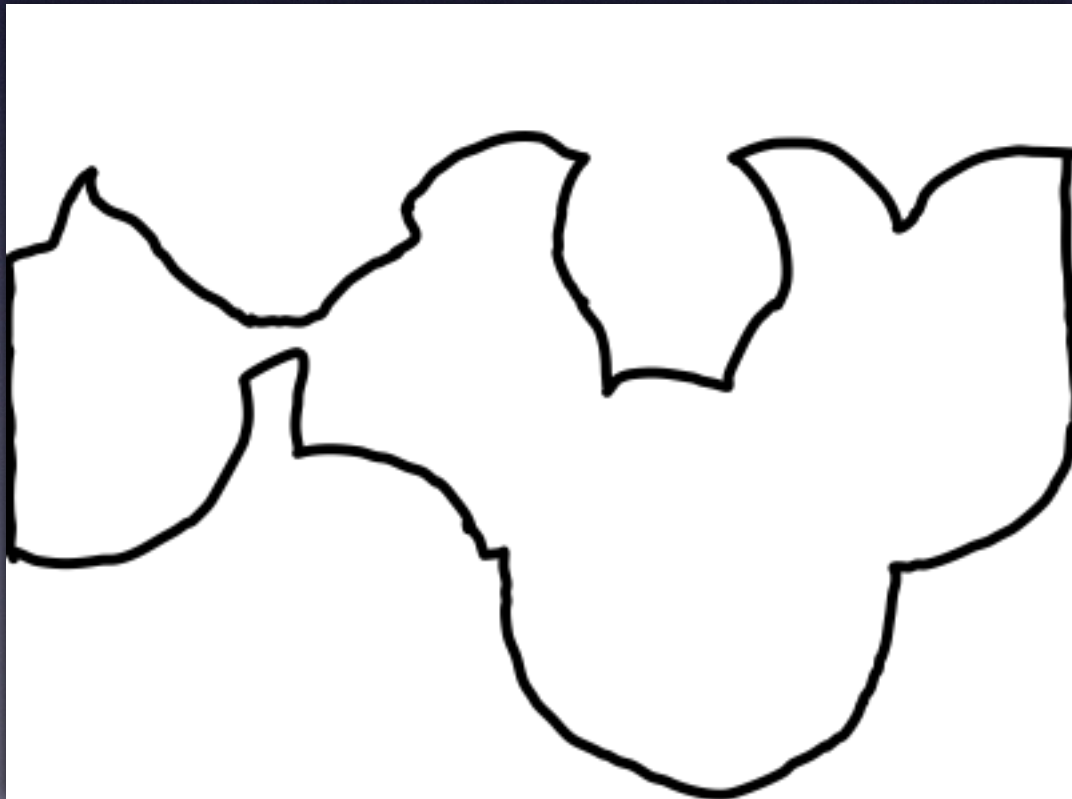
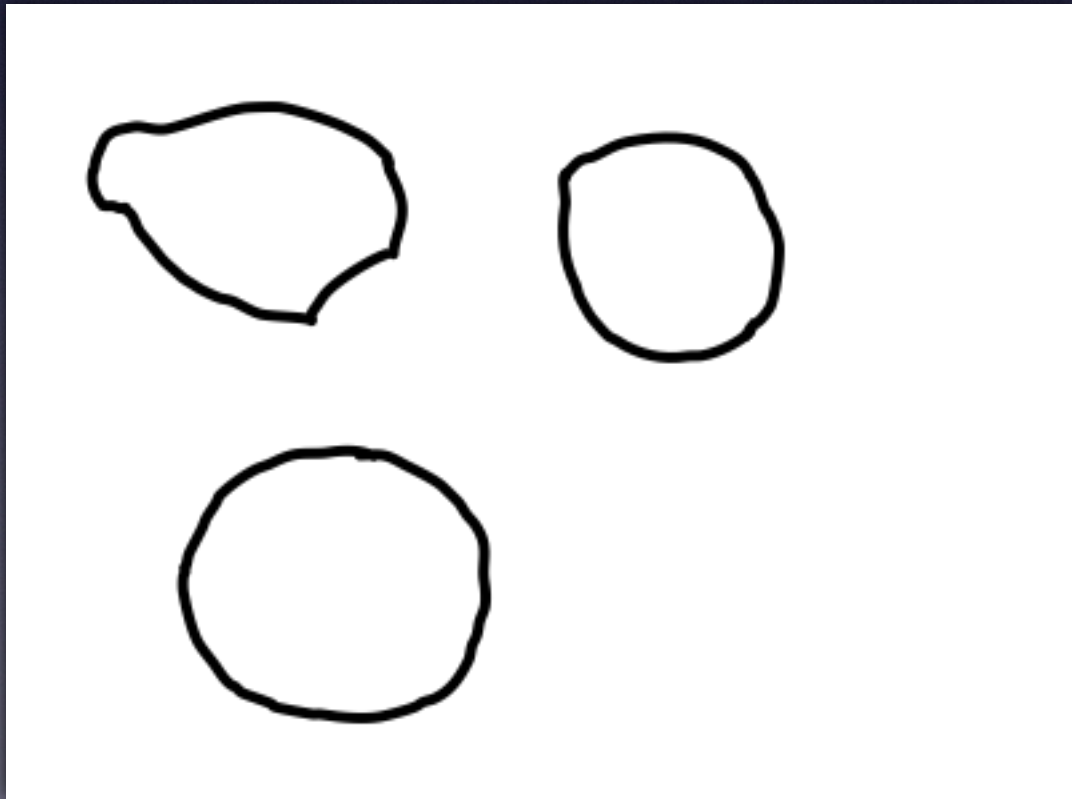
Statistical Models for Visual Detection and Recognition

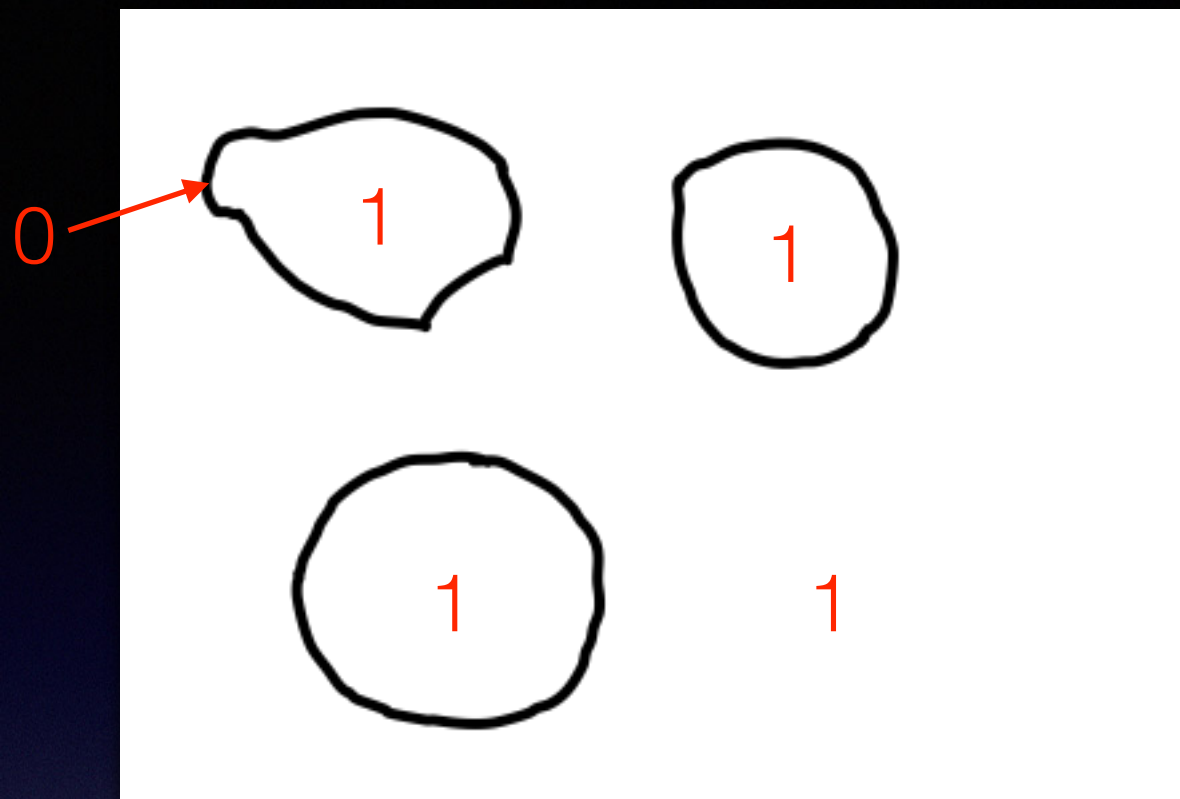
COMPSCI 527

Today: (discrete probabilities)

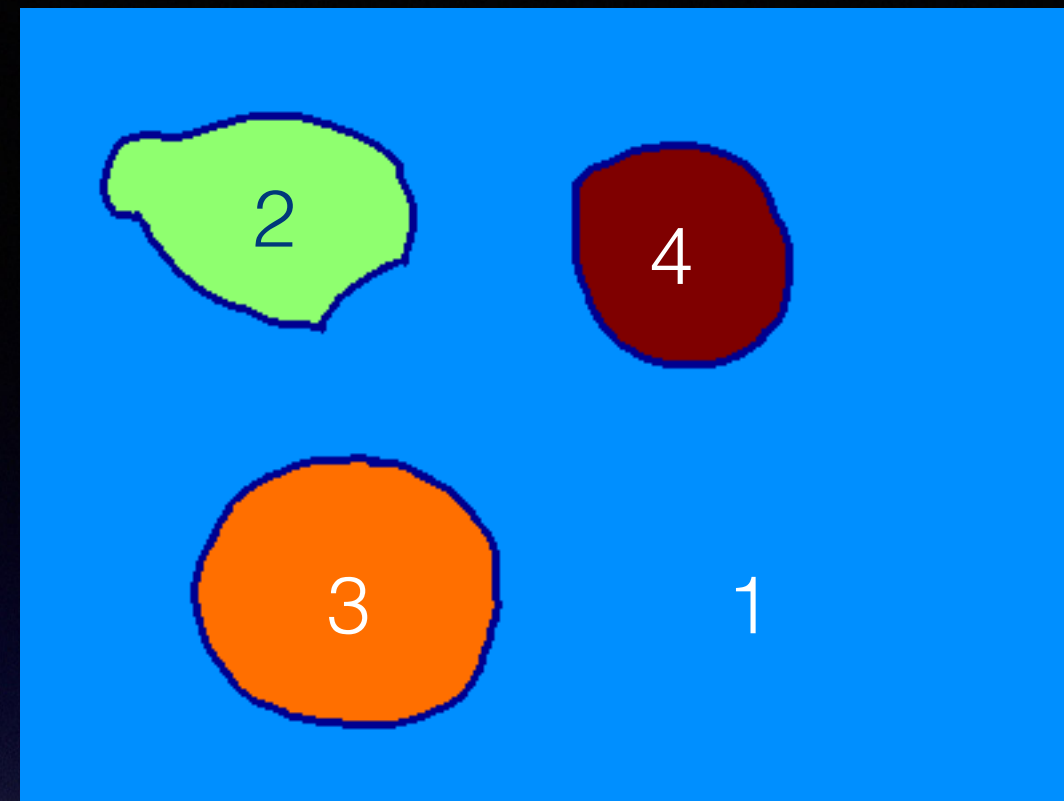
- Color features and Matlab
- Joint and conditional probabilities
- Bayes's theorem and the Bayes classifier



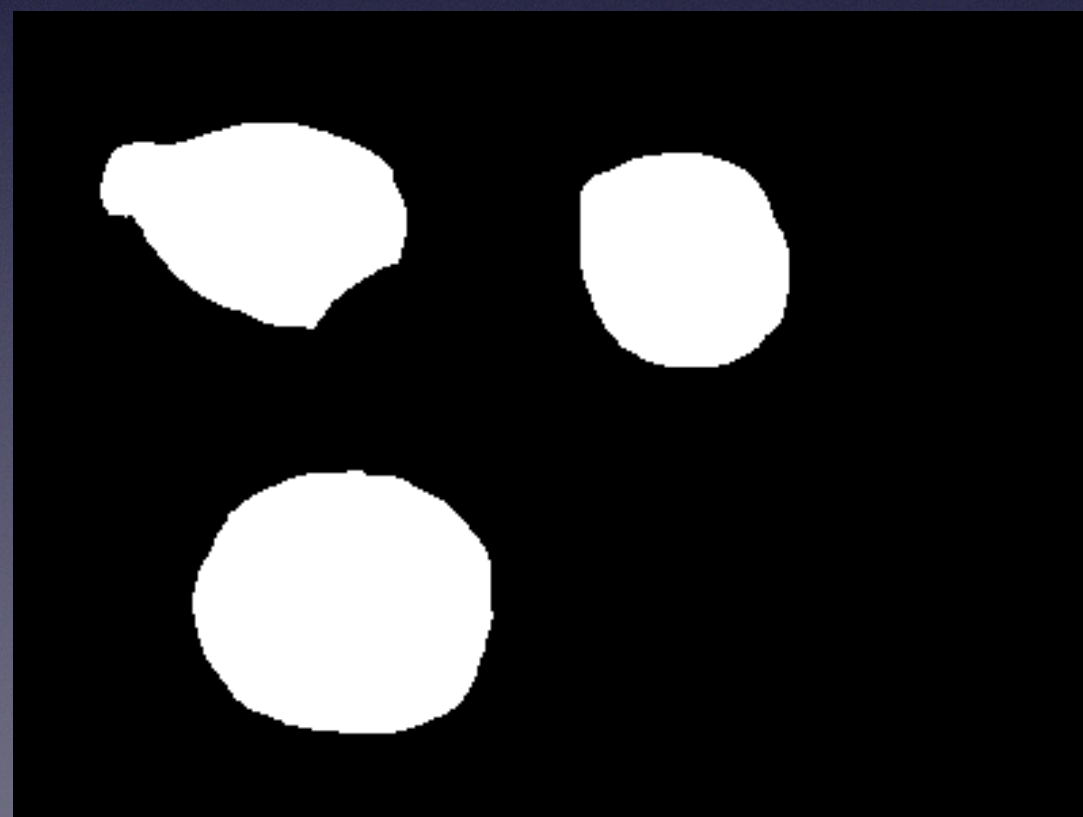




trace



CC



mask

% Connected components

```
cc = bwlabel(trace);
```

```
mask = cc==2 | cc==3 | cc==4;
```

```
red = img(:, :, 1);
```

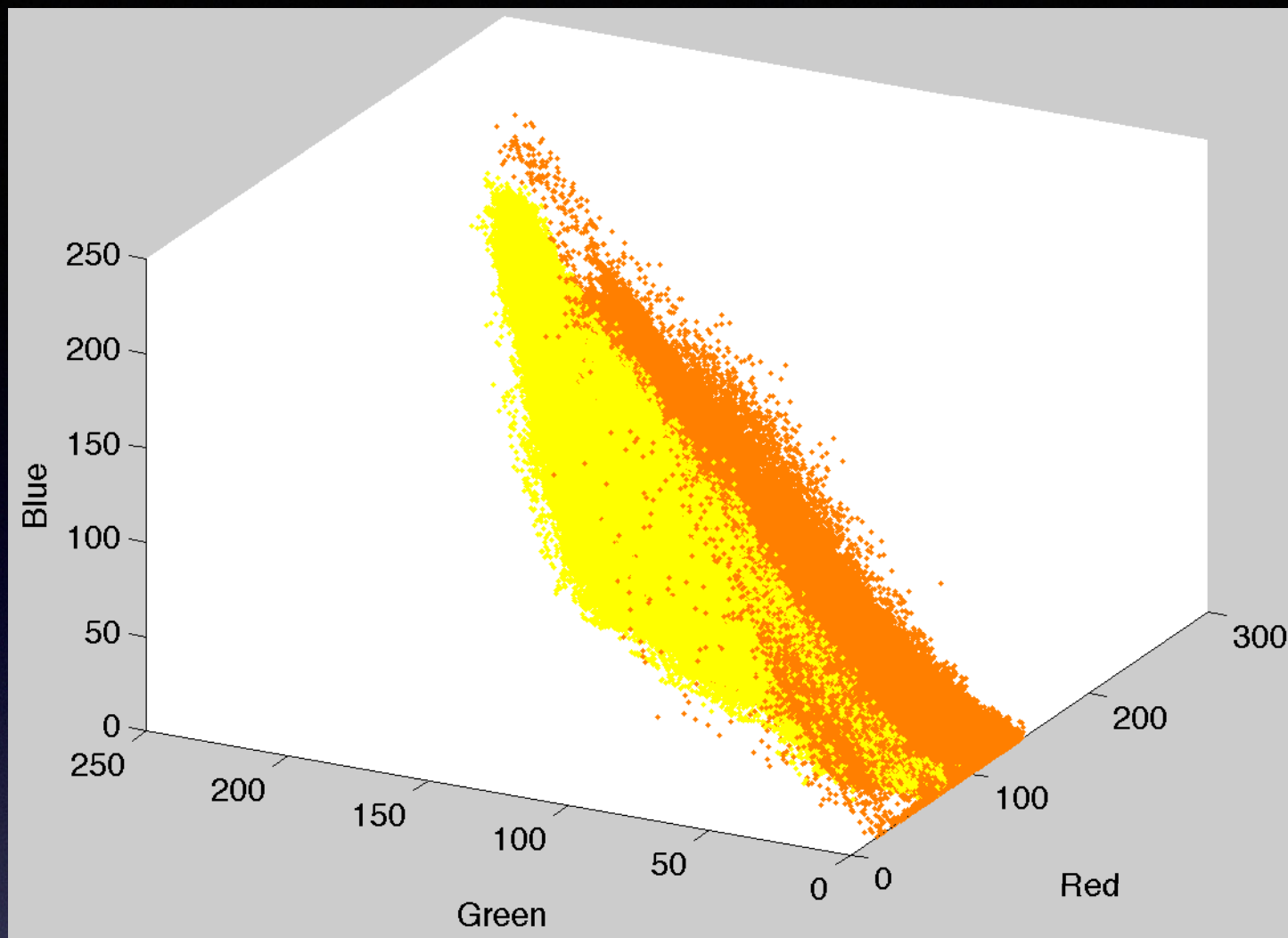
```
green = img(:, :, 2);
```

```
blue = img(:, :, 3);
```

```
rgb = [red(mask), ...
```

```
        green(mask), blue(mask)];
```

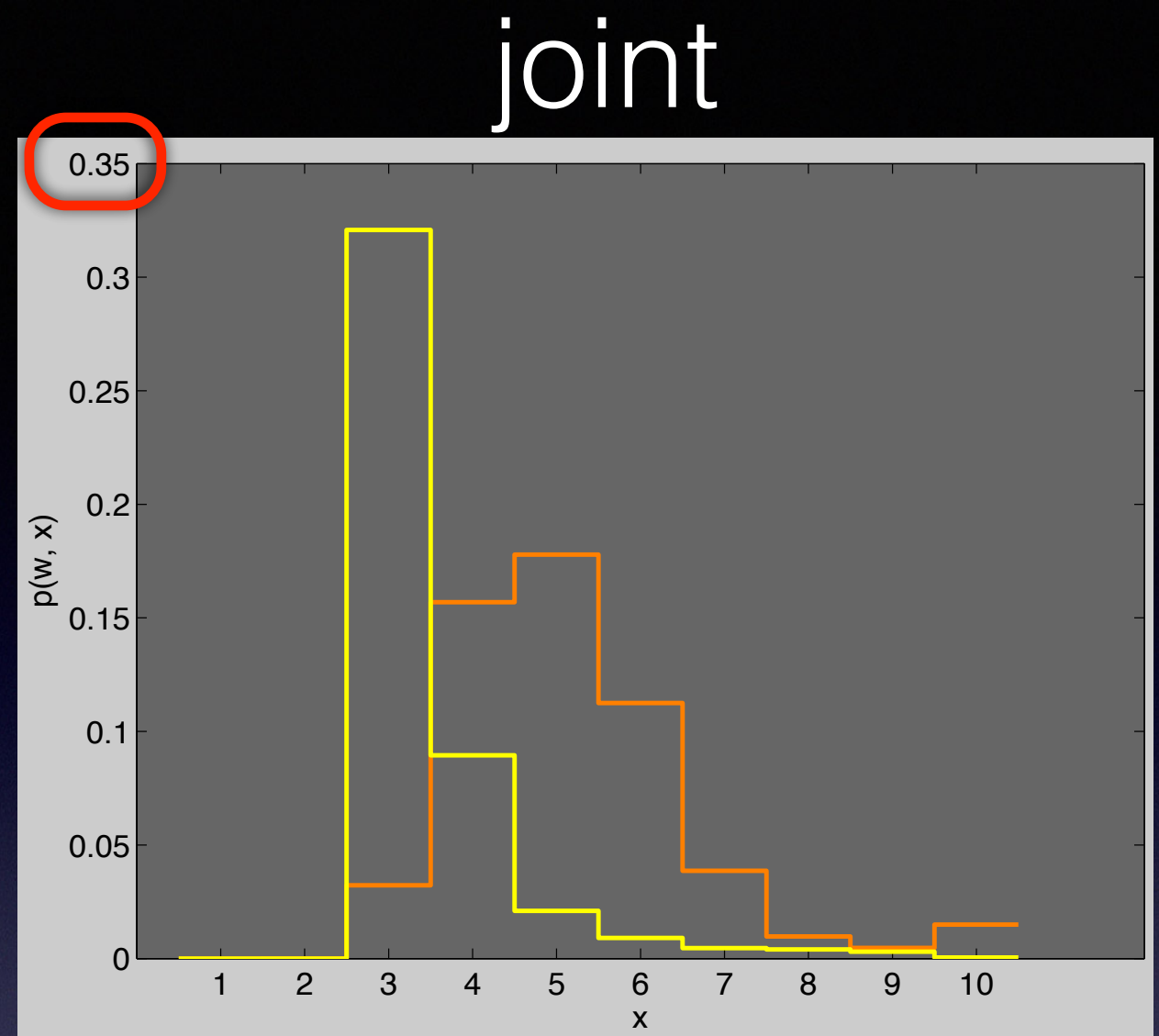
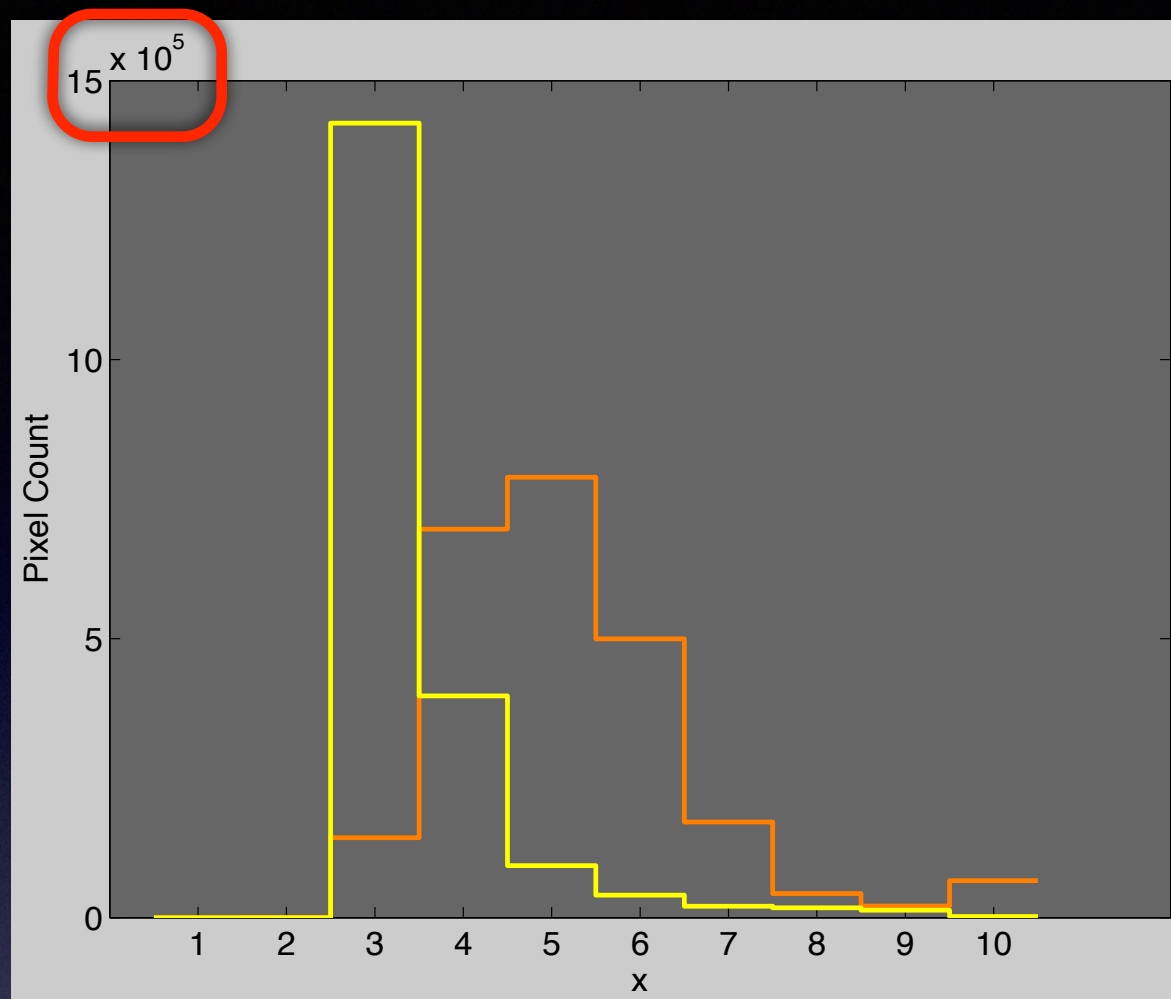
n x 3 array of pixel values



- Brightness does not matter
- Yellow $\propto [1 \ 1 \ 0]$
- Orange $\propto [1 \ 0.5 \ 0]$
- Blue does not matter

$$c = \frac{R - G}{R + G + B}$$

```
function c = colorToScalar(rgb)
rgb = double(rgb);
denom = sum(rgb, 2);
nz = denom ~= 0;
rgb(nz, :) = rgb(nz, :) ./ (denom(nz) * ones(1, 3));
c = rgb(:, 1) - rgb(:, 2);
```

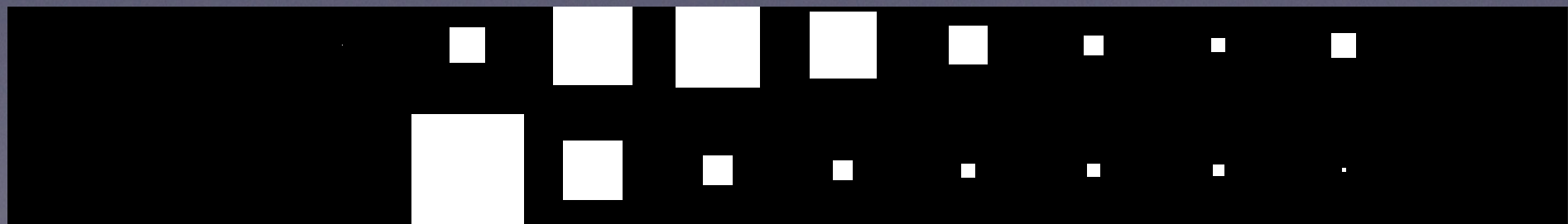



Data *feature*: $x = \text{bin}(c)$
 World *state*: $w = \{O, L\}$

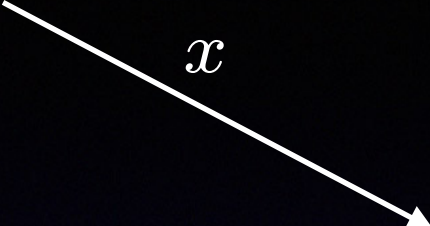
$$\sum_w \sum_x p(w, x) = 1$$

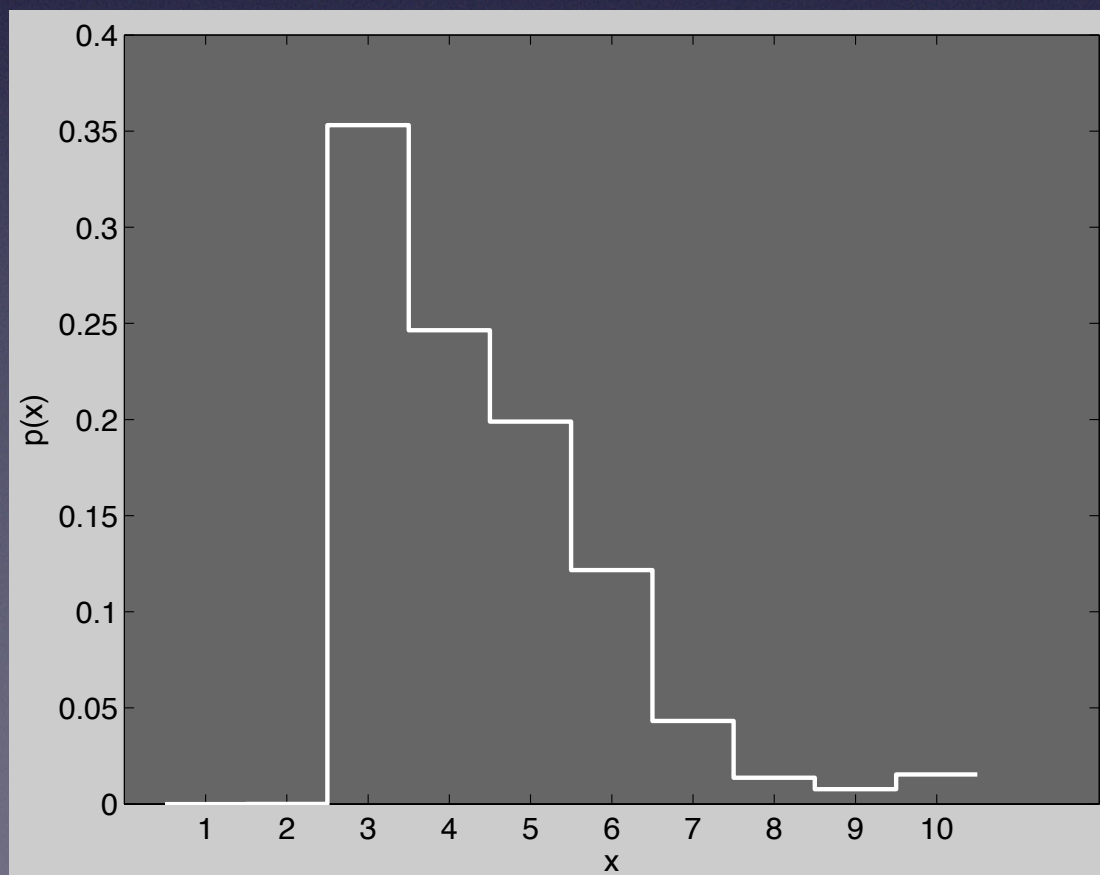
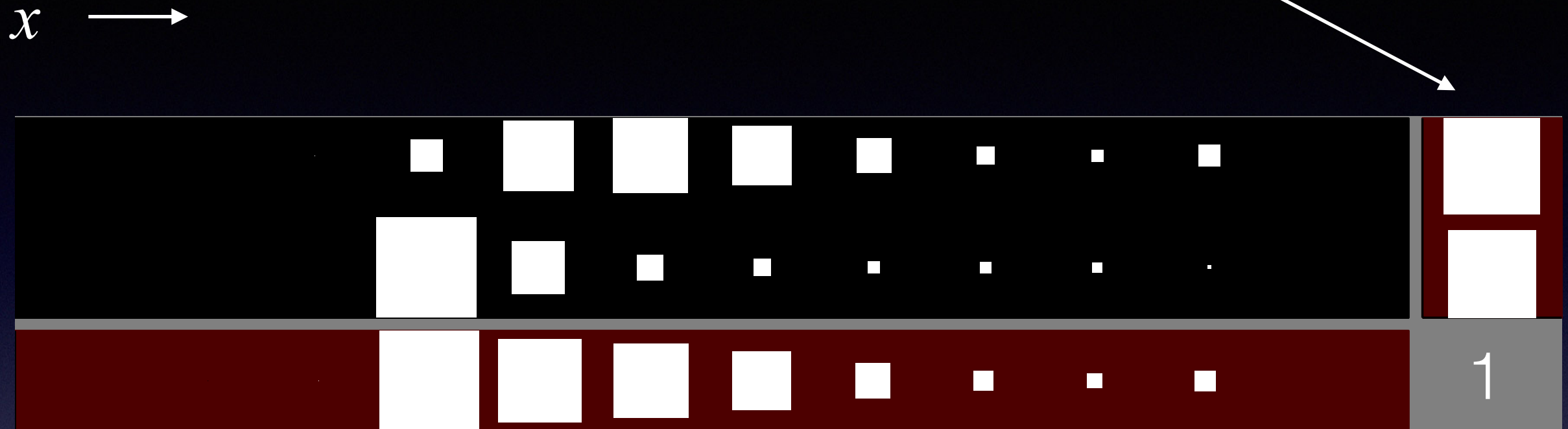
w
 \downarrow
 orange
 lemon


$x \rightarrow$ 1 2 3 4 5 6 7 8 9 10



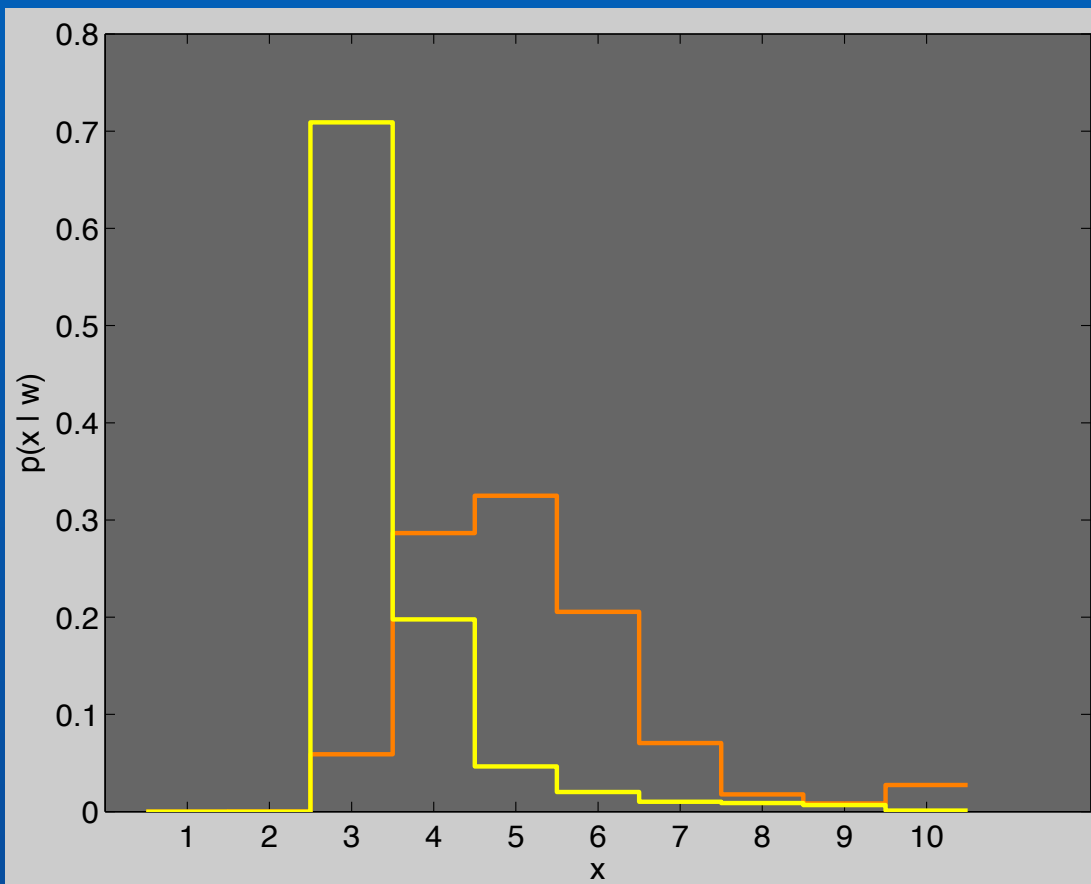
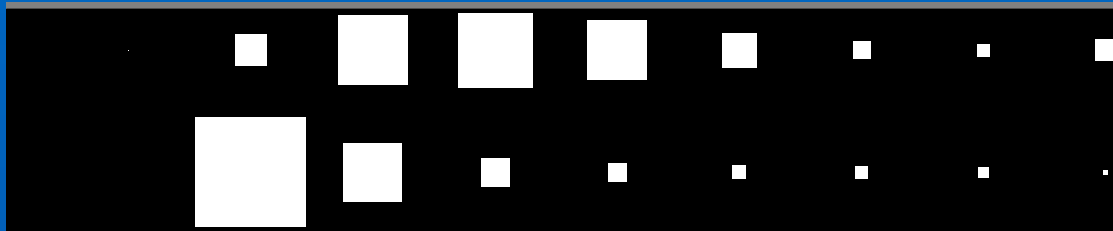
marginals

$$p(w) = \sum_x p(w, x)$$


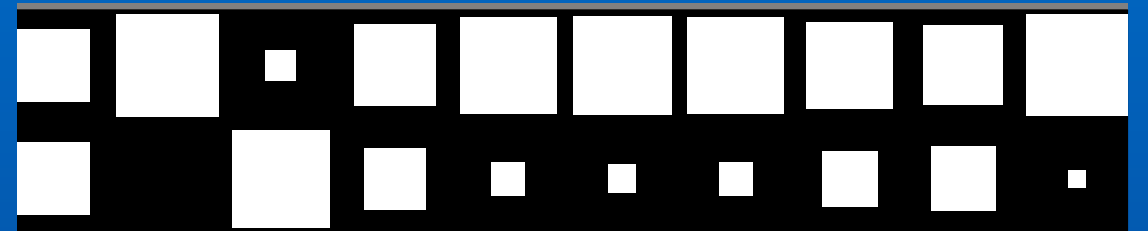


$$p(x) = \sum_w p(w, x)$$


conditionals



$$p(x \mid w) = \frac{p(w, x)}{p(w)}$$



$$p(w \mid x) = \frac{p(w, x)}{p(x)}$$

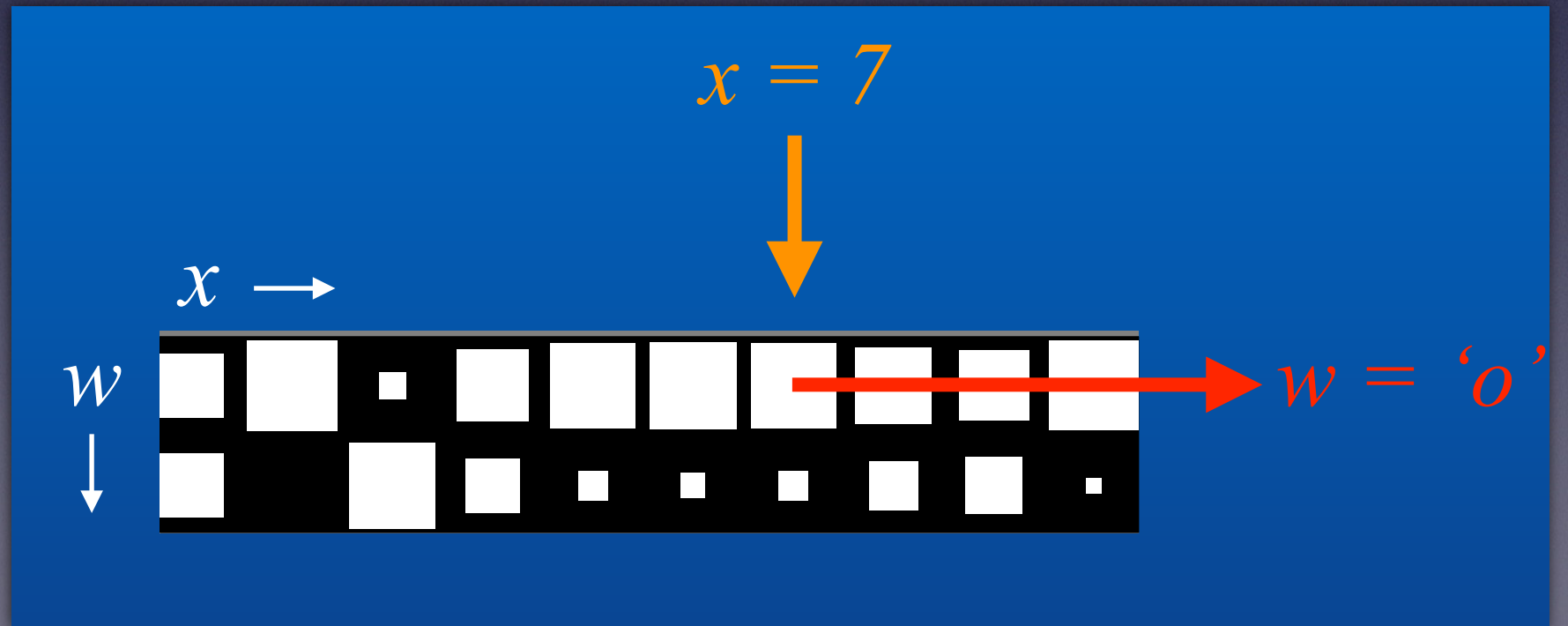
↑
10 of these (b = 1, ... 10)

← 2 of these (f = 1, 2)

The Bayes Classifier

- $w = f(x)$: given an image observation x , find the world state w
- we have $p(w|x)$
- $f(x) = \arg \max_w p(w|x)$

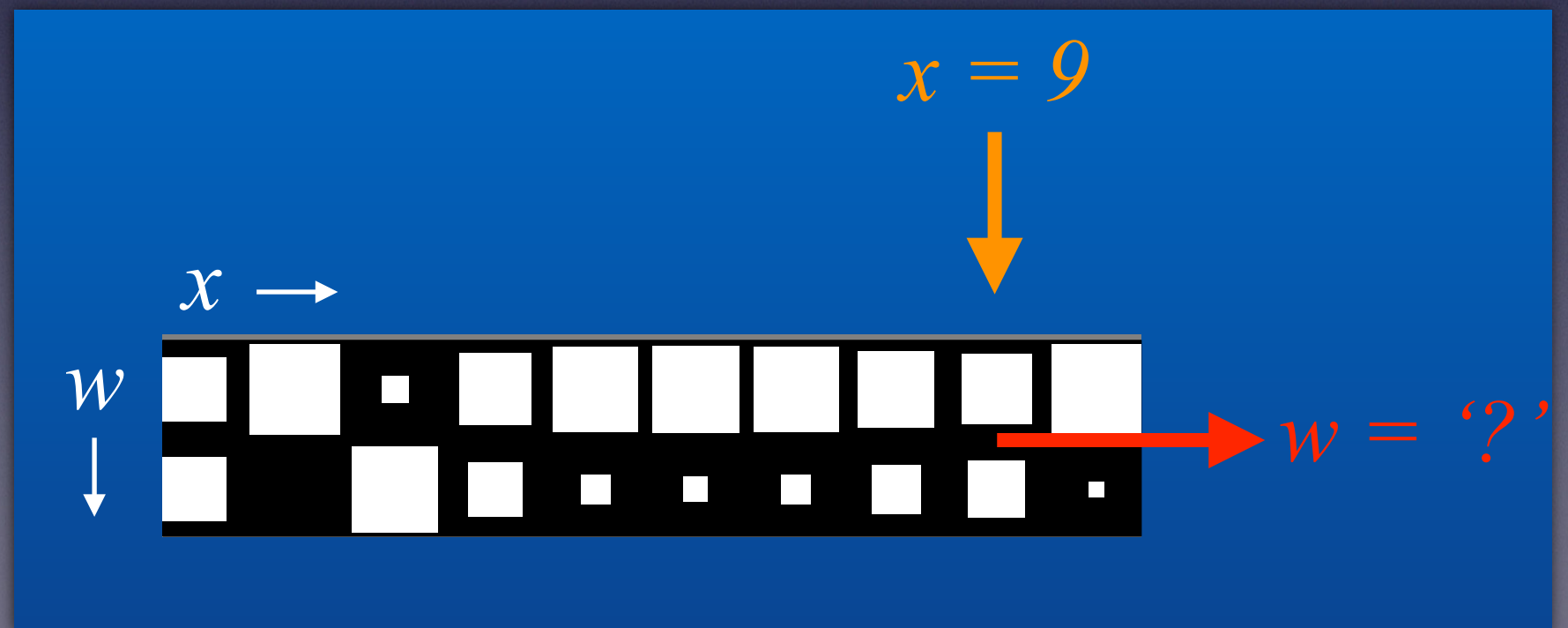
$$p(w \mid x) = \frac{p(w, x)}{p(x)}$$



Classifier with Confidence

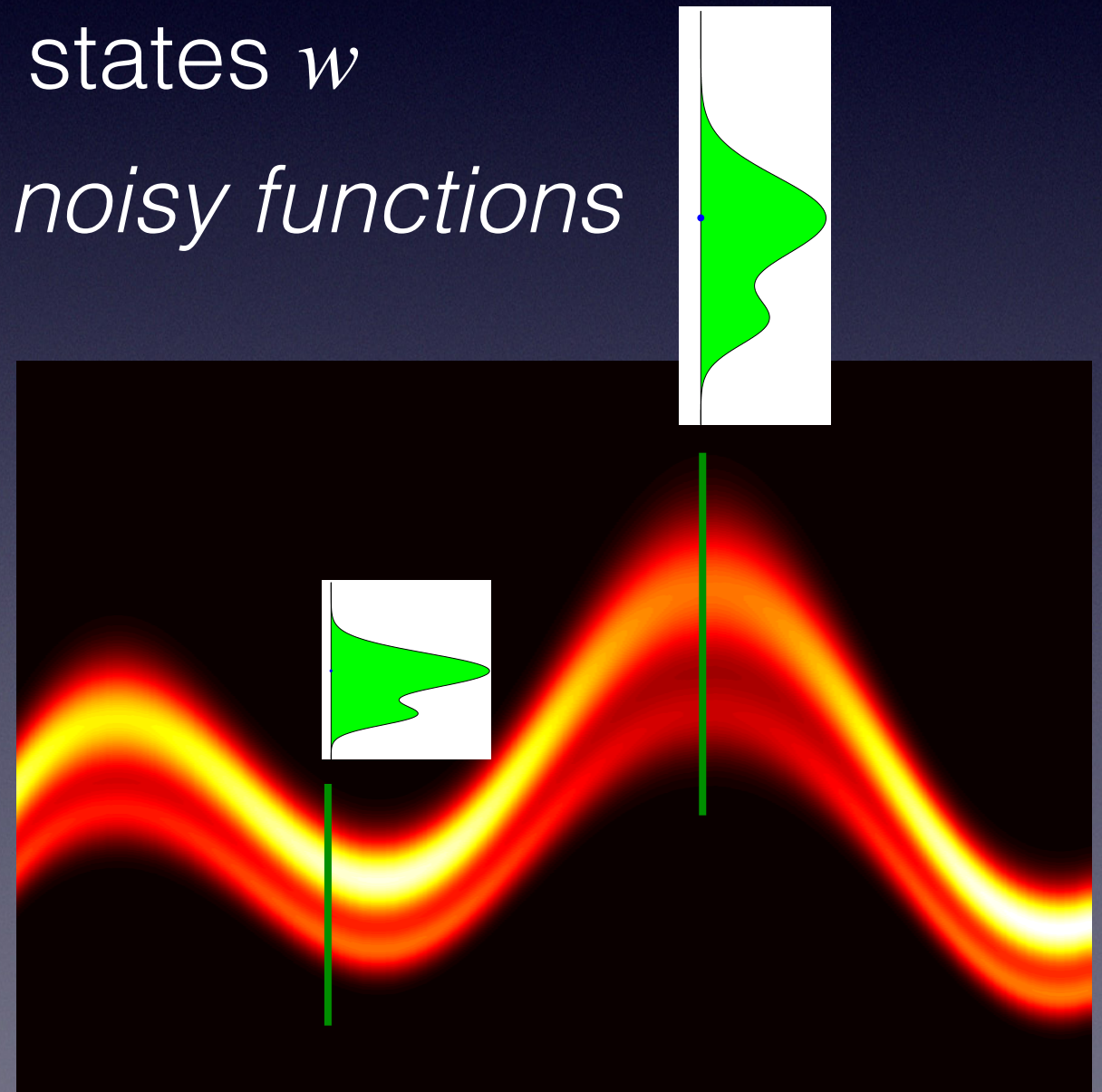
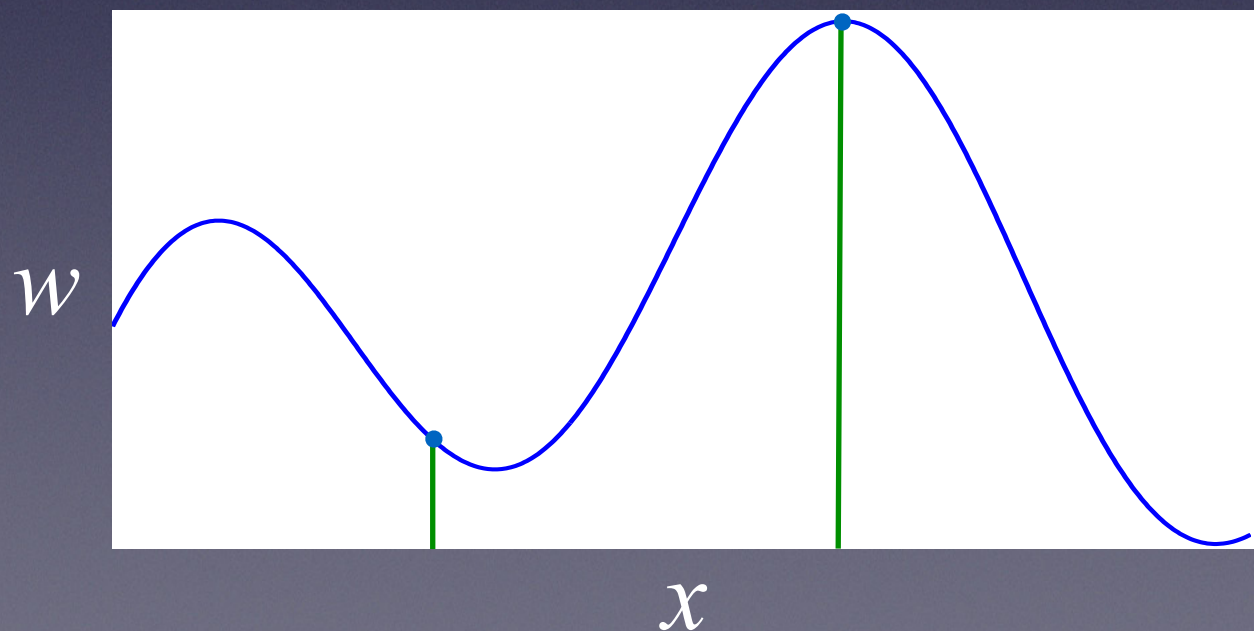
- $f(x) = \arg \max_w p(w|x)$ [Bayes classifier]
- confidence: some function of $p(w|x)$:
maybe $c(x) = 2 [p(f(x)|x) - 1/2]$ for the binary case
- can say “don’t know” if c is too small

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

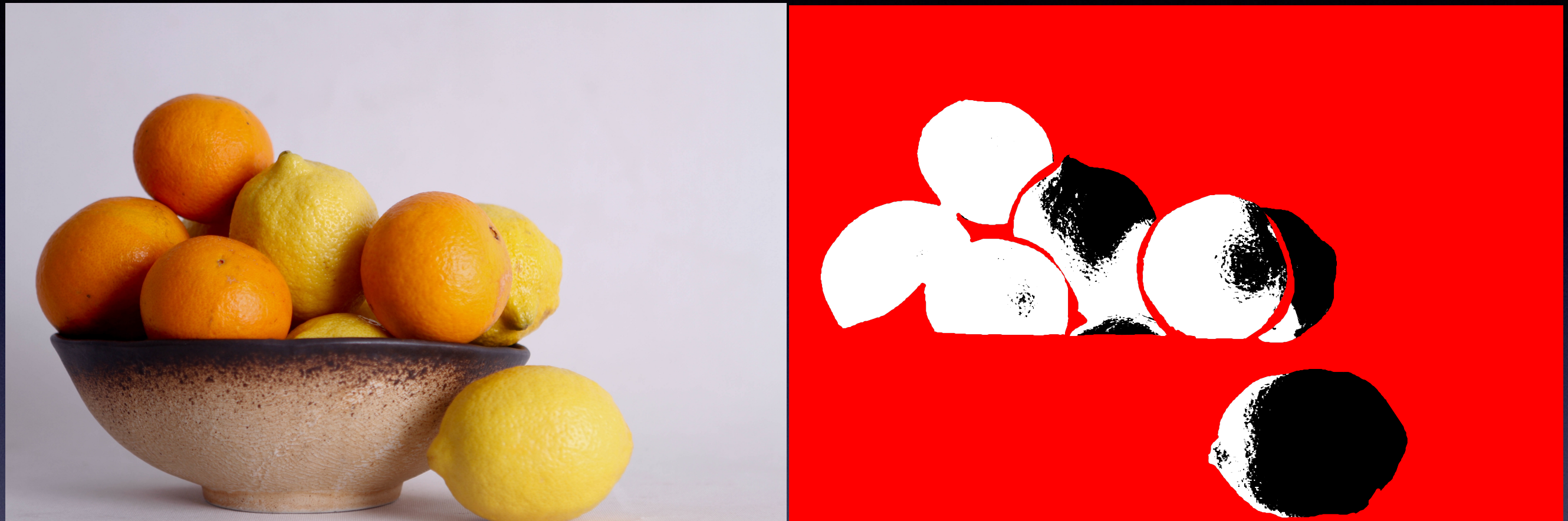


Noisy Functions

- $f(x)$ is a function that maps each image observation x to a world state w
- $p(w|x)$ is a function that maps each image observation x to a distribution over world states w
- conditional probabilities are *noisy functions*



oranges?



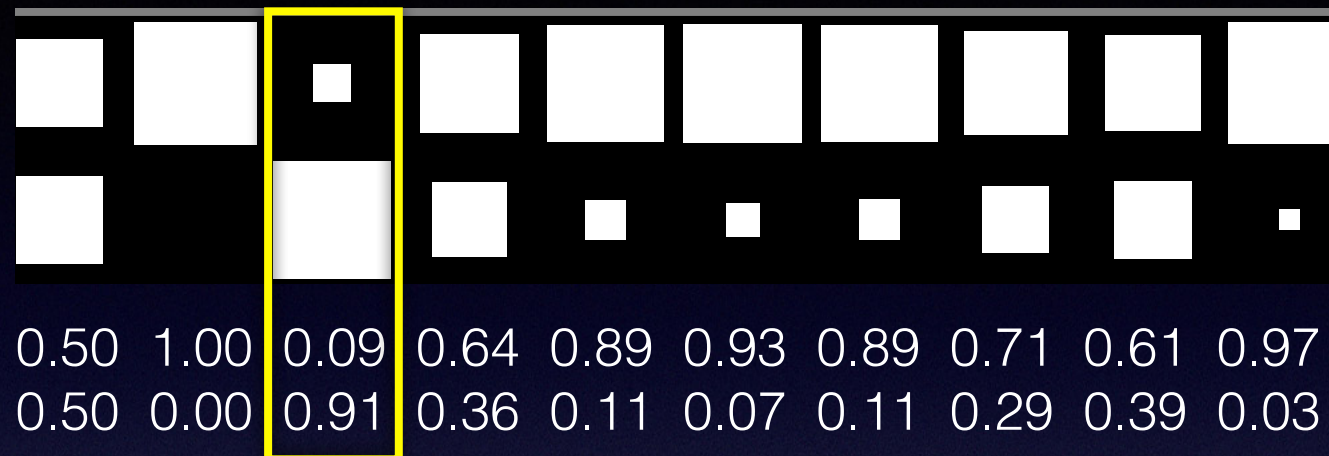
~oranges == lemons?

not really a binary problem!

how well can we possibly do?

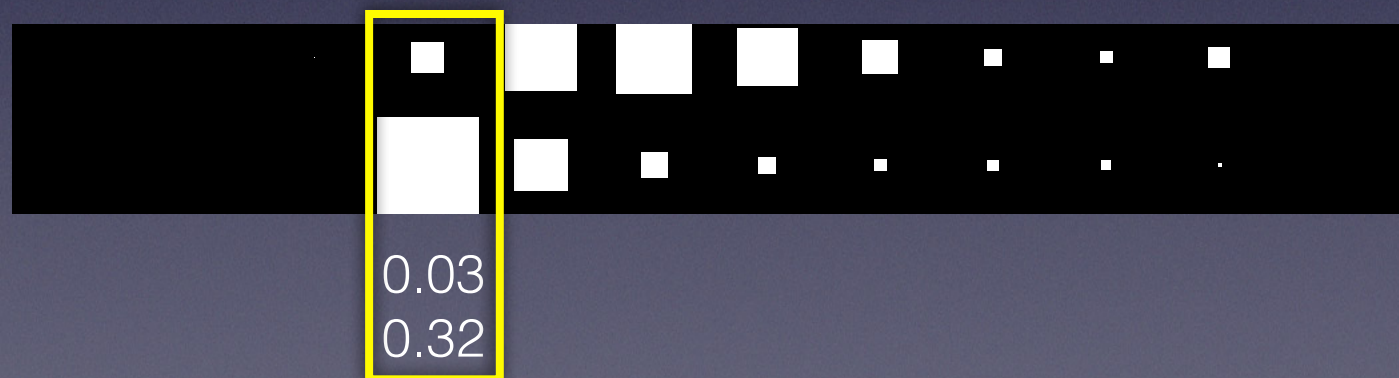
Bayes Error Rate

$p(w|x)$



$$f(x) = \arg \max_w p(w|x)$$

$p(w, x)$



$$e = 1 - \sum_x p(f(x), x) = 0.164$$

Cheating Big Time!



training set

test set

Need: training set \cap test set = \emptyset

Discrete Bayes's Theorem

[one conditional from the other]

$$p(w, x) = p(w \mid x)p(x) = p(x \mid w)p(w)$$

$$p(x \mid w) = \frac{p(w \mid x)p(x)}{p(w)}$$

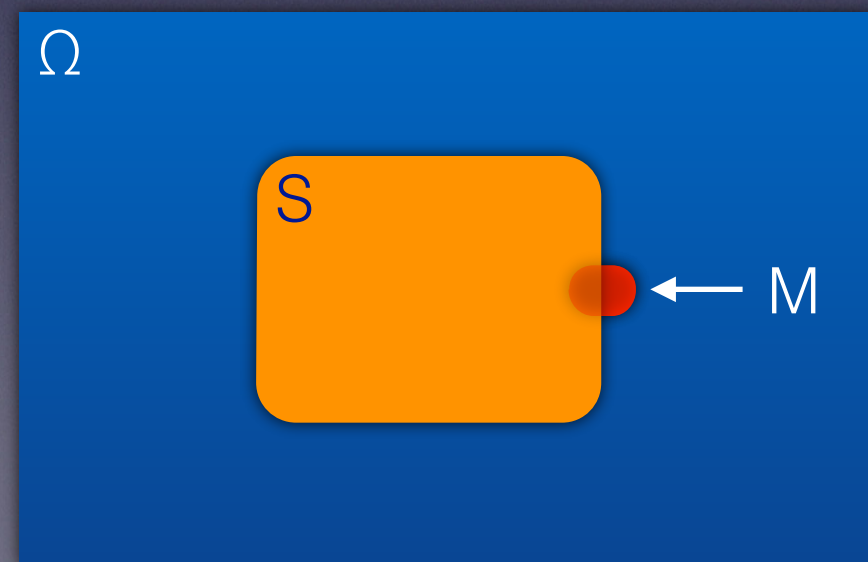
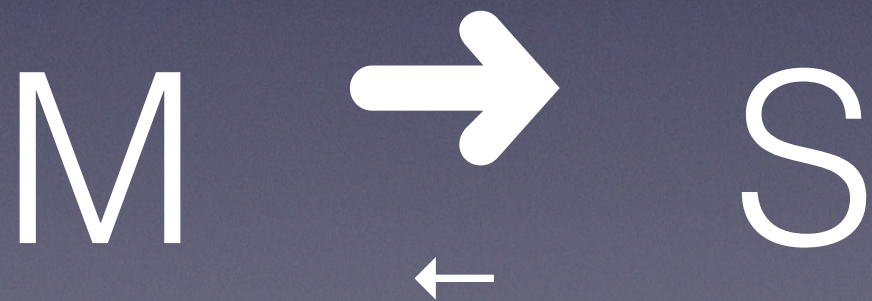
$$p(w \mid x) = \frac{p(x \mid w)p(w)}{p(x)}$$

$$p(x) = \sum_{w'} p(x \mid w')p(w')$$

Bayes Example

[From Russel and Norvig, *Artificial Intelligence*, Prentice Hall 1995]

- One in 20 people have a stiff neck
- One in 50,000 people have meningitis
- *Half the people with meningitis have a stiff neck*
- If you have a stiff neck, should you worry about meningitis?



(world) state data likelihood prior

The diagram illustrates the components of the Bayesian posterior equation. At the top, four terms are listed: "(world) state", "data", "likelihood", and "prior". Below these, the equation $p(w|x) = \frac{p(x|w)p(w)}{p(x)}$ is shown. Green arrows point from "(world) state" to w and from "data" to x in the posterior term $p(w|x)$. Orange arrows point from "likelihood" to $p(x|w)$ and from "prior" to $p(w)$ in the numerator, and from "evidence" to $p(x)$ in the denominator. An orange arrow points from "posterior" to $p(w|x)$.

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

posterior evidence

Convenient Notation Abuse

$$p(w \mid x) = \frac{p(x \mid w)p(w)}{p(x)}$$

Four functions, one name!

$$p_{W|X}(w, x) = \frac{p_{X|W}(x, w)p_W(w)}{p_X(x)}$$

[Note: $p(a, b \mid c, d) = p((a, b) \mid (c, d))$]

[book uses Pr instead of p]