

Ve492: Introduction to Artificial Intelligence

Introduction to Machine Learning



Paul Weng

UM-SJTU Joint Institute

Slides adapted from <http://ai.berkeley.edu>, AIMA, UM

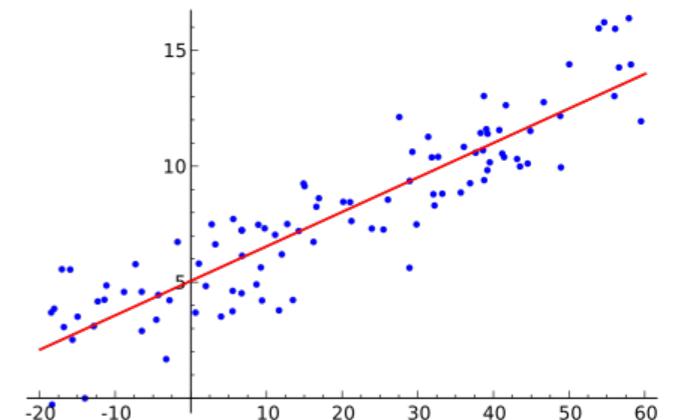
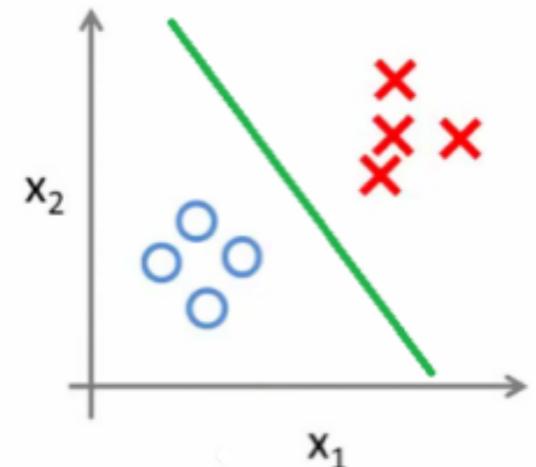
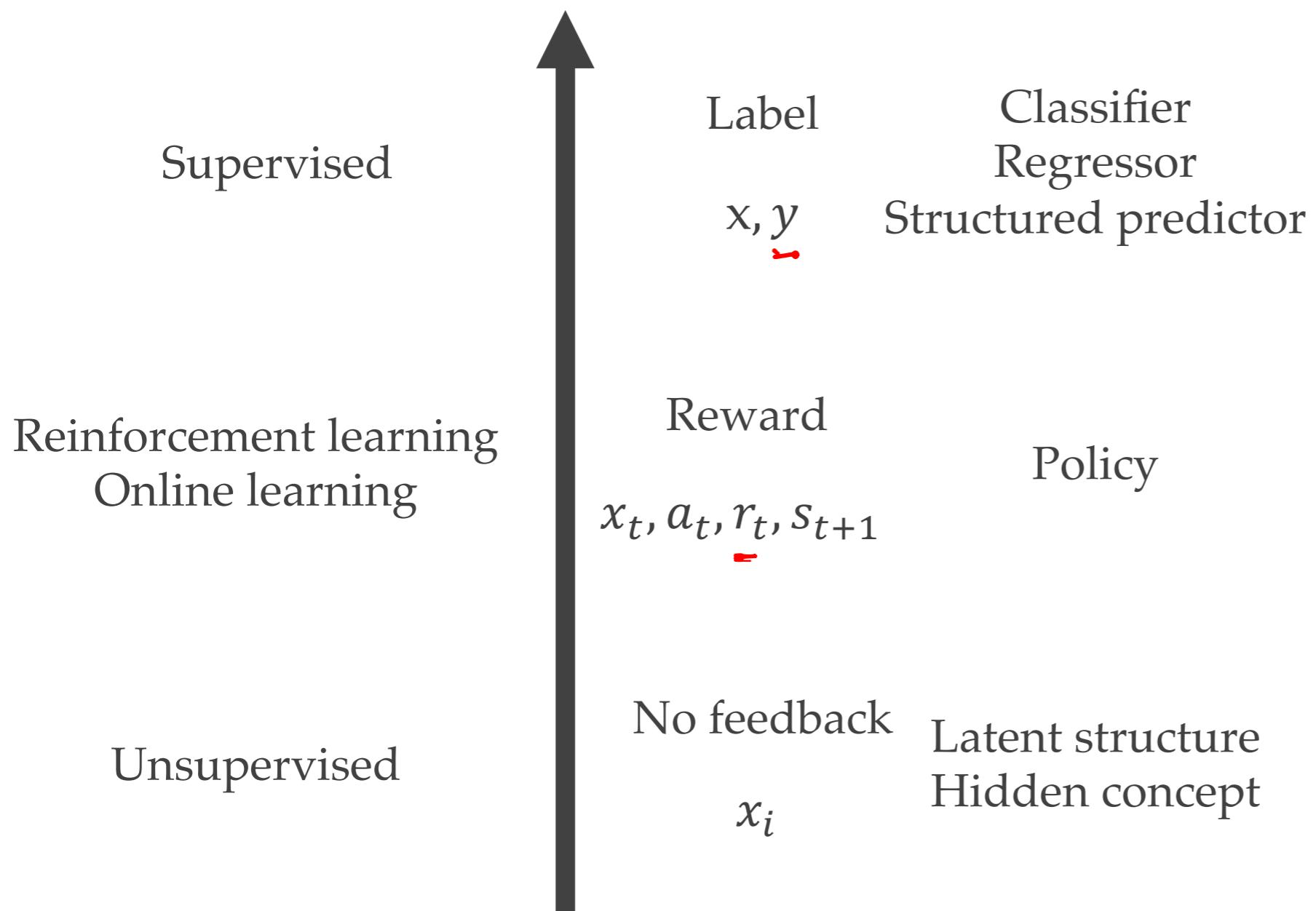
Today

- ❖ Overview of machine learning
- ❖ Naïve Bayes
- ❖ Common issues encountered in machine learning

Machine Learning

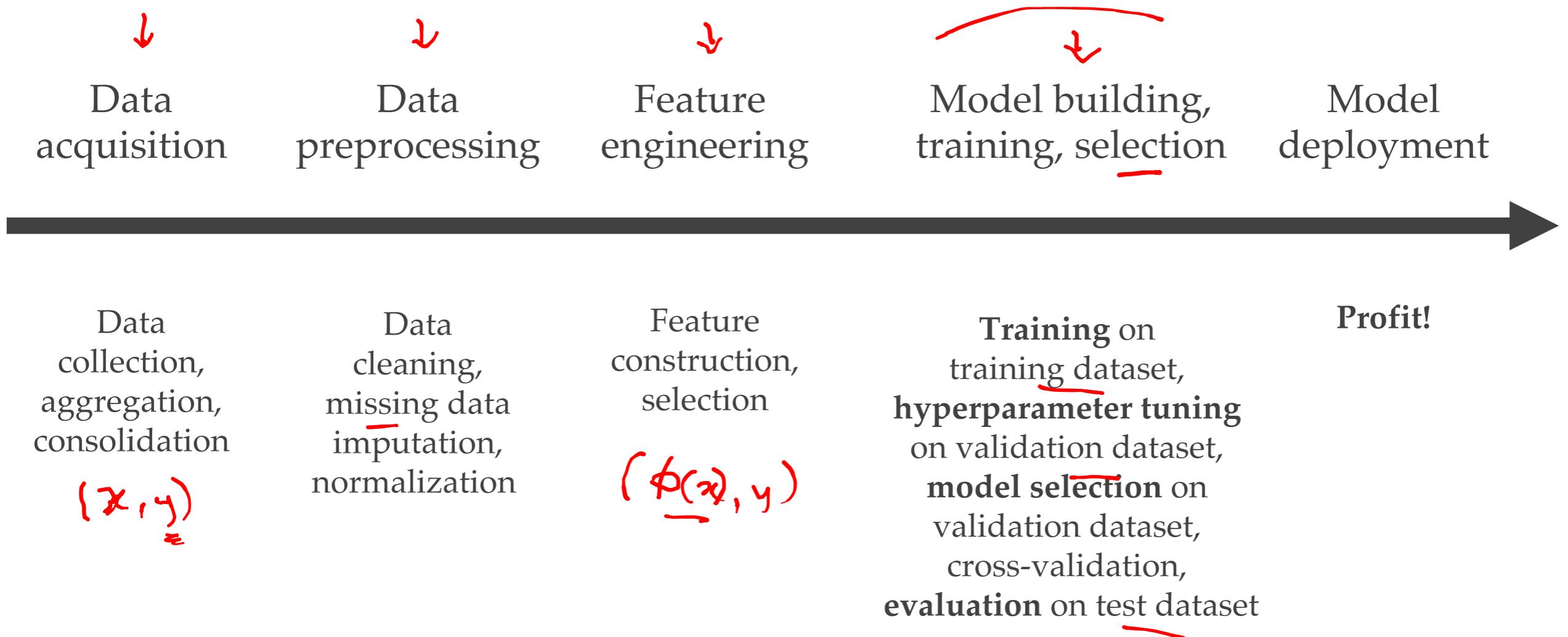
- ❖ Up until now: how use a model to make optimal decisions
- ❖ Machine learning: how to acquire a model from data / experience
 - ❖ Learning parameters (e.g. probabilities)
 - ❖ Learning structure (e.g. BN graphs)
 - ❖ Learning hidden concepts (e.g. clustering)
- ❖ Machine learning: techniques that give a computer system the ability to learn to perform a given task
 - ❖ Learn = improve itself as it sees more data, observations, interactions
- ❖ Machine learning: programming with data

What do we learn from?



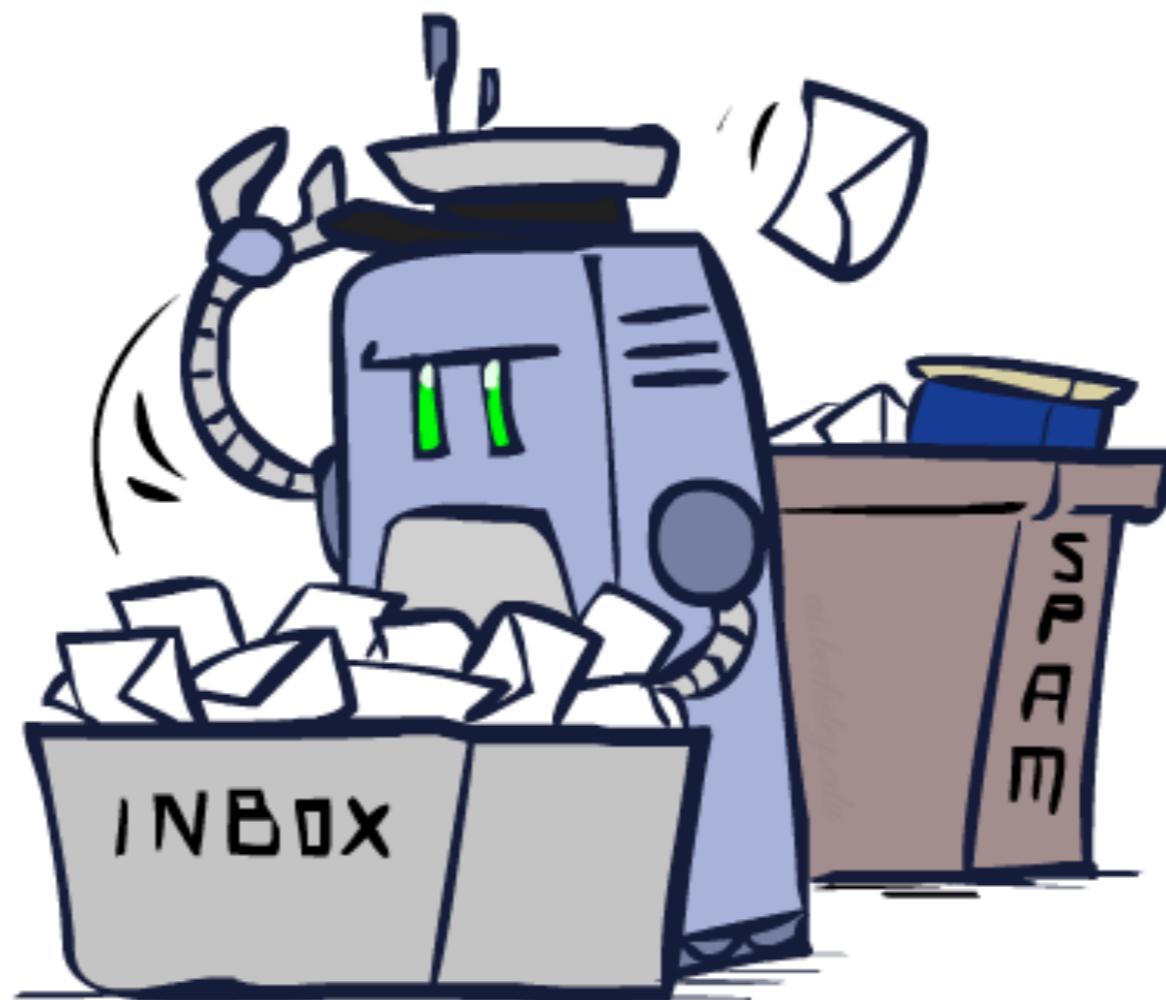
The man at bat readies to swing at the pitch while the umpire looks on.

Typical Supervised ML Pipeline



- ❖ Batch vs online settings

Classification



Example: Spam Filter

- ❖ **Input:** an email x
- ❖ **Output:** spam / ham y

❖ **Setup:**

- ✓ Get a large collection of example emails, each labeled "spam" or "ham"
- ✗ Note: someone has to hand label all this data!
- ❖ Want to learn to predict labels of new, future emails

❖ **Features:** The attributes used to make the ham / spam decision

- ❖ Words: FREE!
- ❖ Text Patterns: \$dd, CAPS
- ❖ Non-text: SenderInContacts
- ❖ ...

$$f(x) \in \mathbb{R}^d \text{ or } \{0, 1\}^d$$

Dear Sir.

First, I must solicit your confidence in this transaction, this is by virtue of its nature as being utterly confidential and top secret. ...

TO BE REMOVED FROM FUTURE MAILINGS, SIMPLY REPLY TO THIS MESSAGE AND PUT "REMOVE" IN THE SUBJECT.

99 MILLION EMAIL ADDRESSES FOR ONLY \$99

Ok, I know this is blatantly OT but I'm beginning to go insane. Had an old Dell Dimension XPS sitting in the corner and decided to put it to use, I know it was working pre being stuck in the corner, but when I plugged it in, hit the power nothing happened.

Example: Digit Recognition

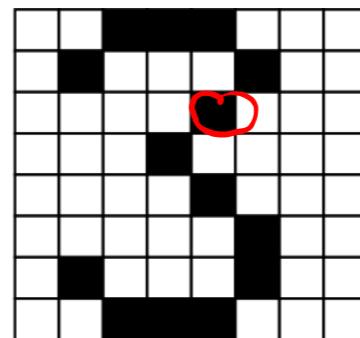
- ❖ **Input:** images / pixel grids
- ❖ **Output:** a digit 0-9

- ❖ **Setup:**

- ❖ Get a large collection of example images, each labeled with a digit
- ❖ Note: someone has to hand label all this data!
- ❖ Want to learn to predict labels of new, future digit images

- ❖ **Features:** The attributes used to make the digit decision

- ❖ Pixels: (6,8)=ON ←
- ❖ Shape Patterns: NumComponents, AspectRatio, NumLoops }
 ... ??



0



1



2



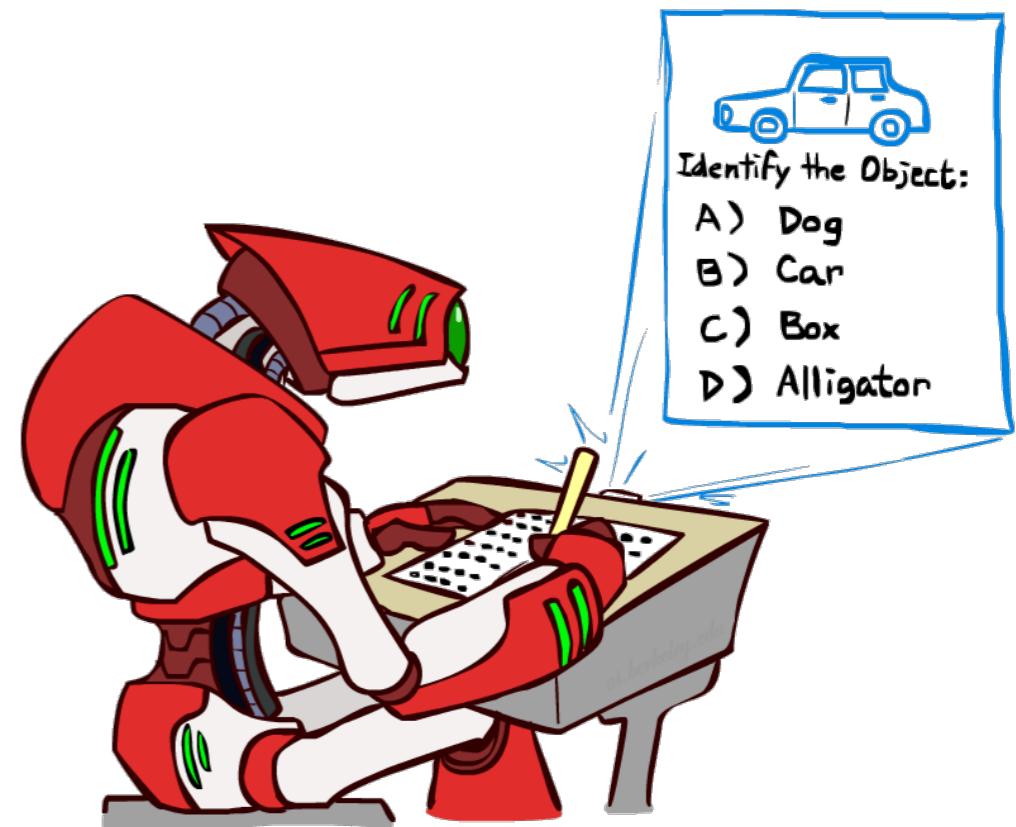
1



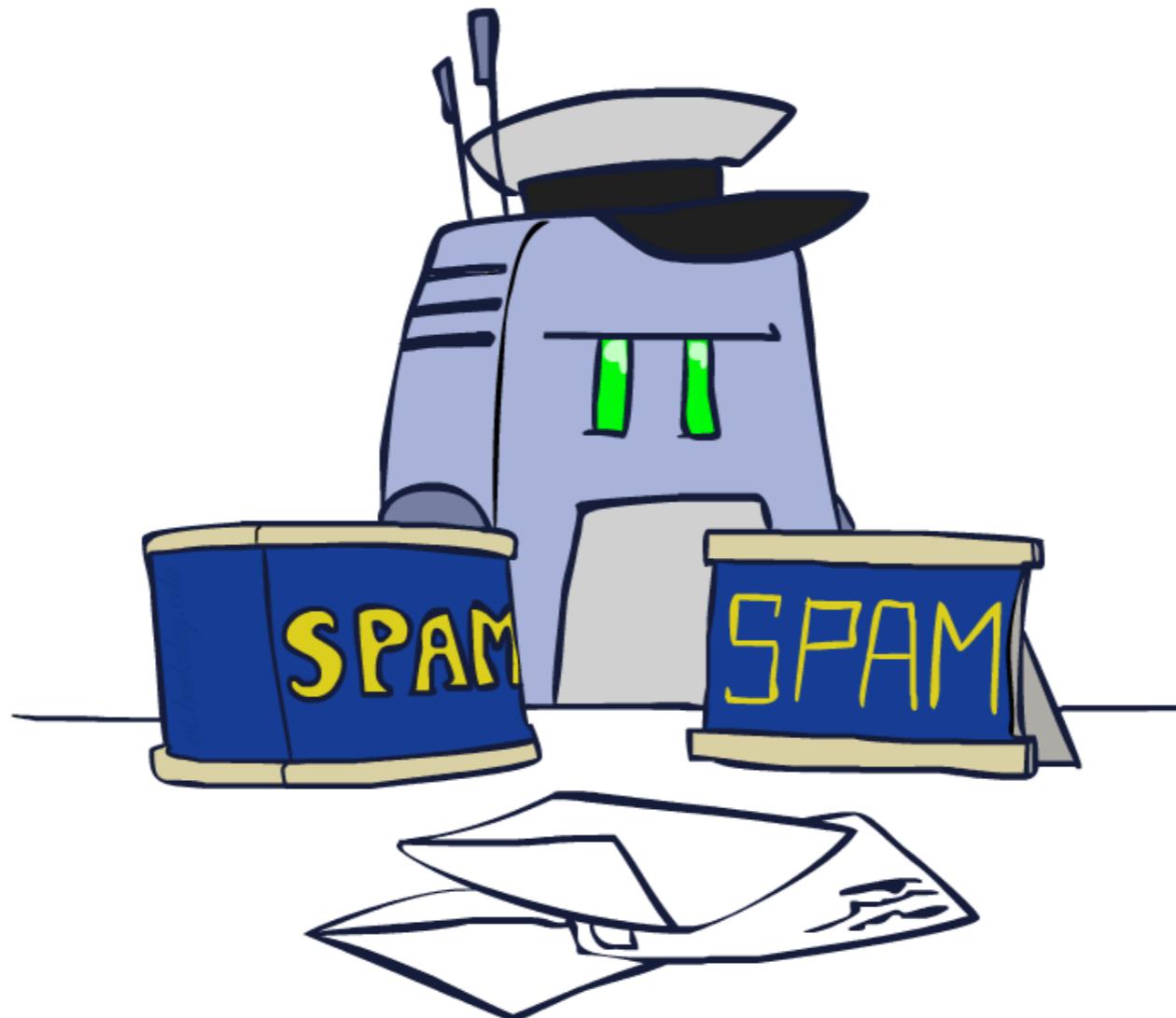
??

Other Classification Tasks

- ❖ Classification: given inputs \underline{x} , predict labels (classes) \underline{y}
- ❖ Examples:
 - ❖ Spam detection (input: document, classes: spam / ham)
 - ❖ OCR (input: images, classes: characters)
 - ❖ Medical diagnosis (input: symptoms, classes: diseases)
 - ❖ Automatic essay grading (input: document, classes: grades)
 - ❖ Fraud detection (input: account activity, classes: fraud / no fraud)
 - ❖ Customer service email routing
 - ❖ ... many more
- ❖ Classification is an important commercial technology!

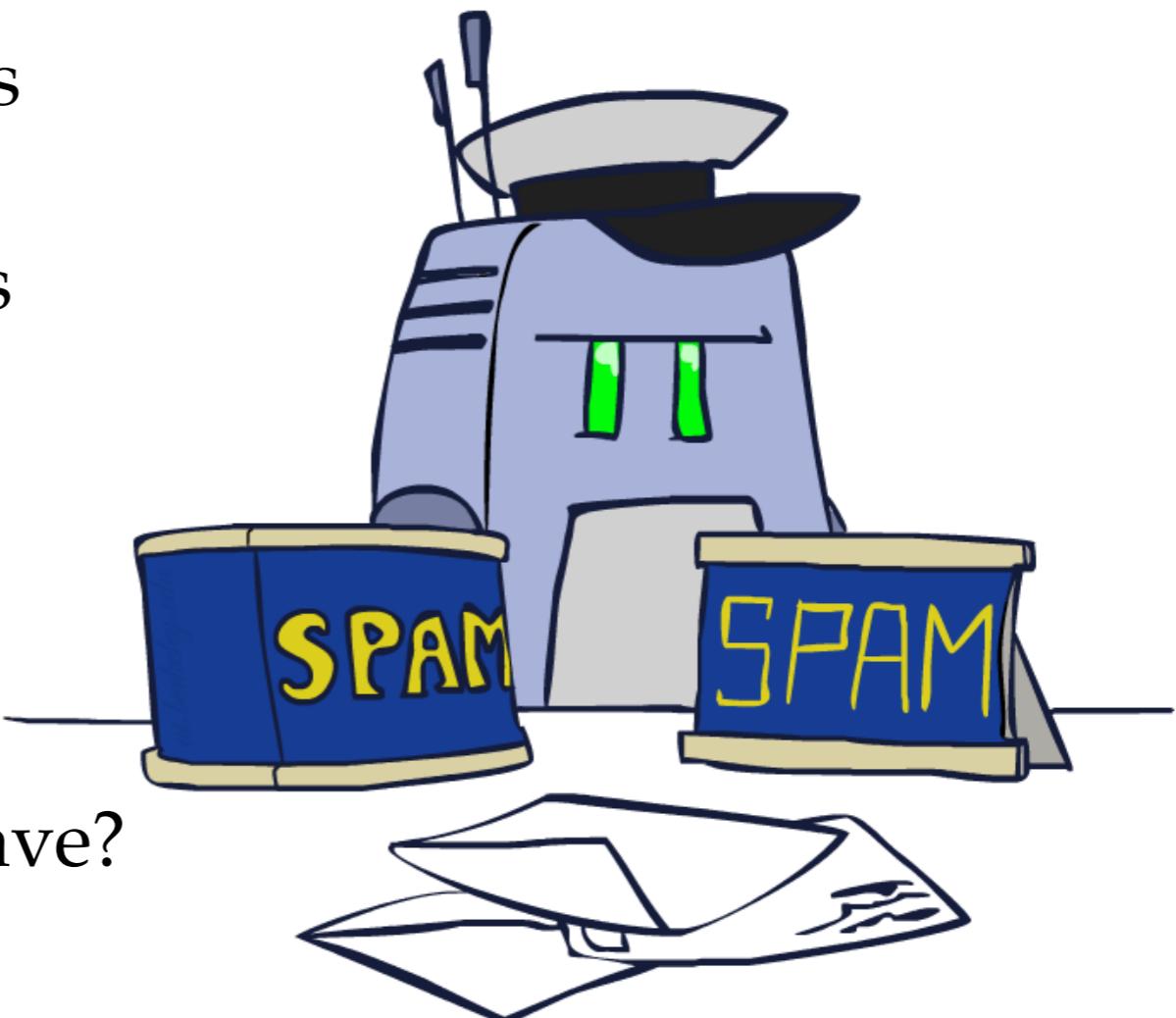


Model-Based Classification



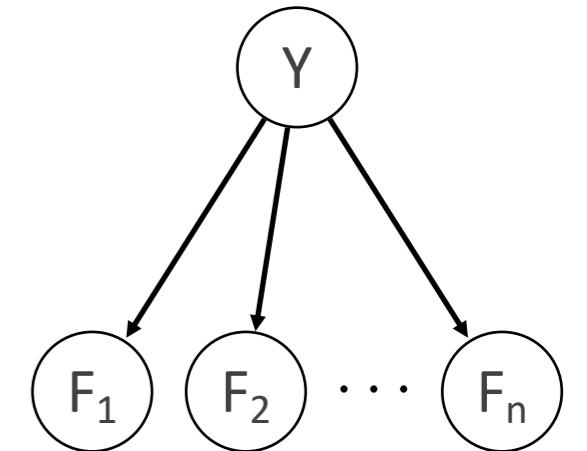
Model-Based Classification

- ❖ Model-based approach
 - ❖ Build a model (e.g. Bayes' net) where both the label and features are random variables
 - ❖ Instantiate any observed features
 - ❖ Query for the distribution of the label conditioned on the features
- ❖ Challenges
 - ❖ What structure should the BN have?
 - ❖ How should we learn its parameters?



Naïve Bayes for Digits

- ❖ **Naïve Bayes:** Assume all features are independent effects of the label
- ❖ Simple digit recognition version:
 - ❖ One feature (variable) F_{ij} for each grid position $\langle i,j \rangle$
 - ❖ Feature values are on off , based on whether intensity is more or less than 0.5 in underlying image
 - ❖ Each input maps to a feature vector, e.g.
- ❖ Here: lots of features, each is binary valued
- ❖ Naïve Bayes model: $P(Y|F_{0,0} \dots F_{15,15}) \propto P(Y) \prod_{i,j} P(F_{i,j}|Y)$
- ❖ What do we need to learn? 16×16



$\rightarrow \langle F_{0,0} = 0 \ F_{0,1} = 0 \ F_{0,2} = 1 \ F_{0,3} = 1 \ F_{0,4} = 0 \ \dots \ F_{15,15} = 0 \rangle$

joint

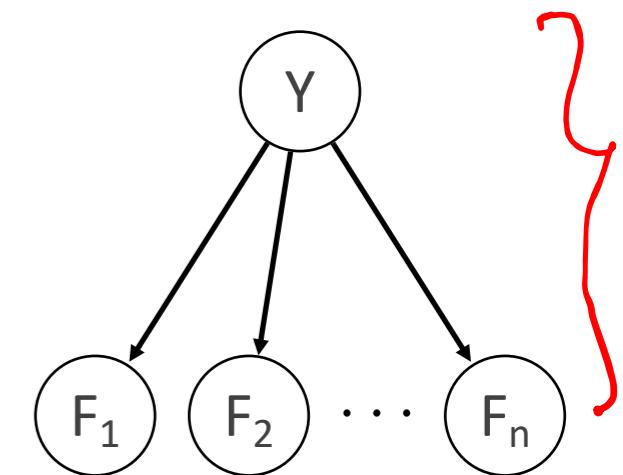
General Naïve Bayes

- ❖ A general Naive Bayes model:

$$P(Y, F_1 \dots F_n) = P(Y) \prod_i P(F_i|Y)$$

$|Y|$
parameters
 $|Y| \times |F|^n$ values
 $n \times |F| \times |Y|$
parameters

$\mathcal{O}(|Y||F|^n)$ $\mathcal{O}(\underline{n}|F||Y|^2)$



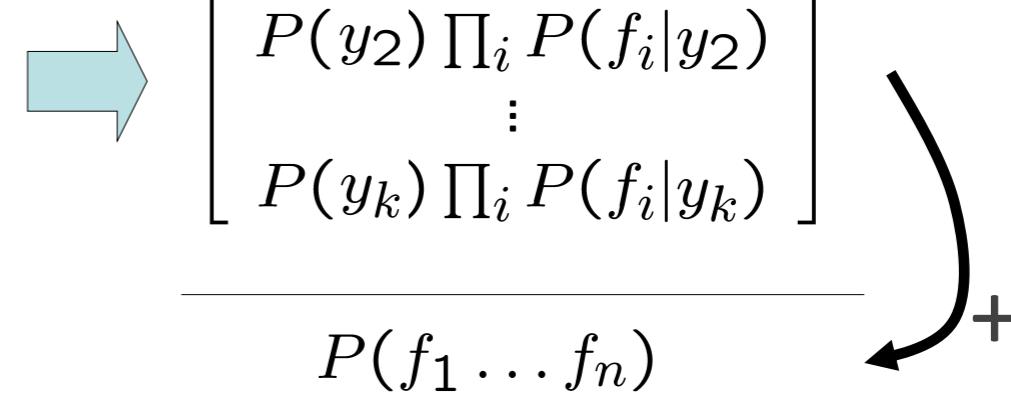
- ❖ We only have to specify how each feature depends on the class
- ❖ Total number of parameters is *linear* in n
- ❖ Model is very simplistic, but often works anyway

Inference for Naïve Bayes

- ❖ **Goal:** compute posterior distribution over label variable Y
 - ❖ **Step 1:** get joint probability of label and evidence for each label

$$P(\underbrace{Y, f_1 \dots f_n}_{\text{---}}) = \begin{bmatrix} P(y_1, f_1 \dots f_n) \\ P(y_2, f_1 \dots f_n) \\ \vdots \\ P(y_k, f_1 \dots f_n) \end{bmatrix} \xrightarrow{\quad} \frac{\begin{bmatrix} P(y_1) \prod_i P(f_i|y_1) \\ P(y_2) \prod_i P(f_i|y_2) \\ \vdots \\ P(y_k) \prod_i P(f_i|y_k) \end{bmatrix}}{P(f_1 \dots f_n)}$$

+



- ❖ **Step 2:** sum to get probability of evidence $P(Y|f_1 \dots f_n)$
- ❖ **Step 3:** normalize by dividing Step 1 by Step 2

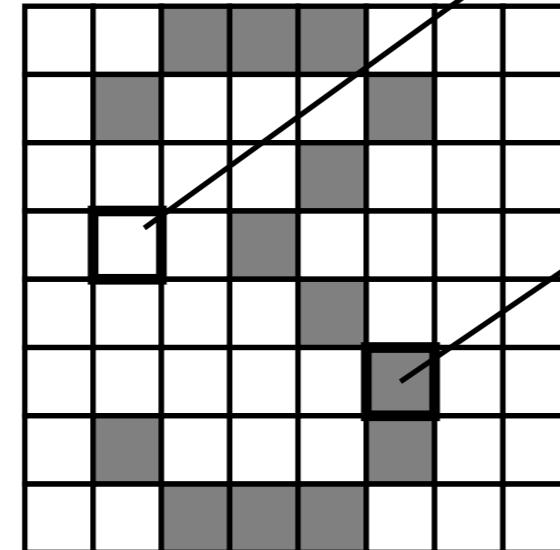
General Naïve Bayes

- ❖ What do we need in order to use Naïve Bayes?
 - ❖ Inference method (we just saw this part)
 - ❖ Start with a bunch of probabilities: $P(Y)$ and the $P(F_i | Y)$ tables
 - ❖ Use standard inference to compute $P(Y | F_1 \dots F_n)$
 - ❖ Nothing new here
 - ❖ Estimates of local (conditional) probability tables
 - { ❖ $P(Y)$, the prior over labels
 - ❖ $P(F_i | Y)$ for each feature (evidence variable)
 - ❖ These probabilities are collectively called the *parameters* of the model and denoted by θ
 - ❖ Up until now, we assumed these were given, but...
 - ❖ ...they typically come from training data counts: we'll look at this soon

Example: Conditional Probabilities

$P(Y)$

1	0.1
2	0.1
3	0.1
4	0.1
5	0.1
6	0.1
7	0.1
8	0.1
9	0.1
0	0.1



$P(F_{3,1} = on|Y) \quad P(F_{5,5} = on|Y)$

1	0.01
2	0.05
3	0.05
4	0.30
5	0.80
6	0.90
7	0.05
8	0.60
9	0.50
0	0.80

1	0.05
2	0.01
3	0.90
4	0.80
5	0.90
6	0.90
7	0.25
8	0.85
9	0.60
0	0.80

Example: Spam Filter

- ❖ Naïve Bayes spam filter

- ❖ Data:

- ❖ Collection of emails, labeled spam or ham
- ❖ Note: someone has to hand label all this data!
- ❖ Split into training, validation, test sets

- ❖ Classifiers

- ❖ Learn on the training set
- ❖ (Tune it on a validation set)
- ❖ Test it on new emails

Dear Sir.

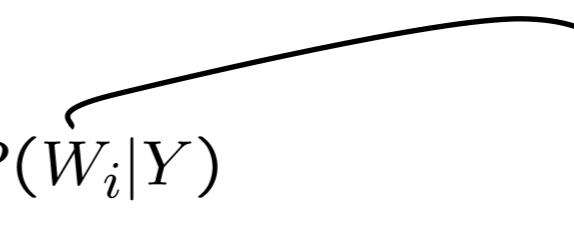
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Naïve Bayes for Text

- ❖ Bag-of-words Naïve Bayes: how many variables are there?
 - ❖ Features: W_i is the word at position i how many values?
 - ❖ As before: predict label conditioned on feature variables (spam vs. ham)
 - ❖ As before: assume features are conditionally independent given label
 - ❖ New: each W_i is identically distributed
- ❖ Generative model:
$$P(Y, W_1 \dots W_n) = P(Y) \prod_i P(W_i|Y)$$


Word at position i , not i^{th} word in the dictionary!
- ❖ “Tied” distributions and bag-of-words
 - ❖ Usually, each variable gets its own conditional probability distribution $P(F|Y)$
 - ❖ In a bag-of-words model
 - ❖ Each position is identically distributed
 - ❖ All positions share the same conditional probs $P(W|Y)$ 
 - ❖ Why make this assumption?
 - ❖ Called “bag-of-words” because model is insensitive to word order or reordering

in is lecture lecture next over person remember room
sitting the the to to up wake when you

Example: Spam Filtering

- ❖ Model: $P(Y, W_1 \dots W_n) = P(Y) \prod_i P(W_i|Y)$

- ❖ What are the parameters?

$P(Y)$	$P(W \text{spam})$	$P(W \text{ham})$
ham : 0.66 spam: 0.33	the : 0.0156 to : 0.0153 and : 0.0115 of : 0.0095 you : 0.0093 a : 0.0086 with: 0.0080 from: 0.0075 ...	the : 0.0210 to : 0.0133 of : 0.0119 2002: 0.0110 with: 0.0108 from: 0.0107 and : 0.0105 a : 0.0100 ...

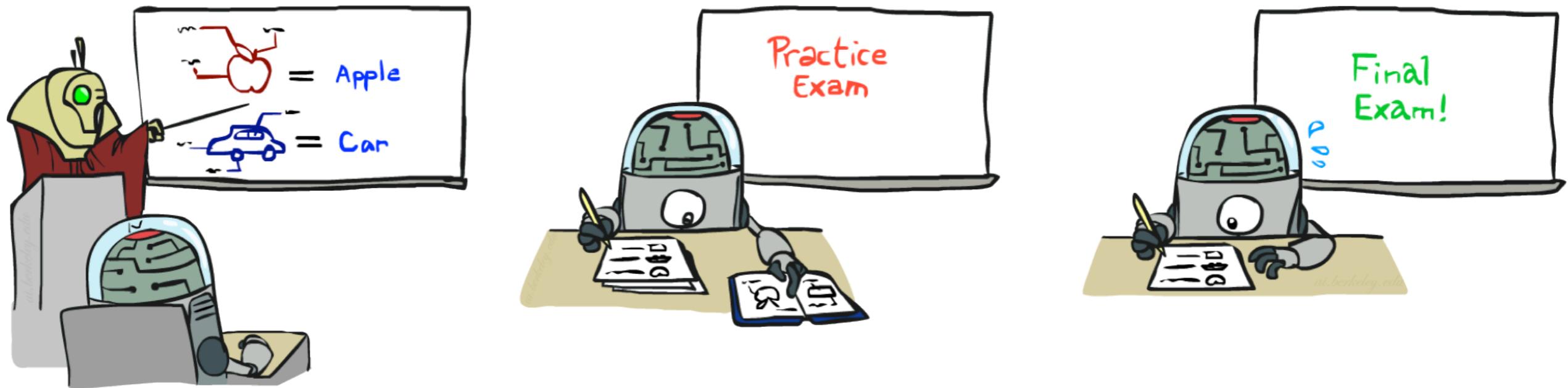
- ❖ Where do these tables come from?

Spam Example

	Word	P(w spam)	P(w ham)	Tot Spam	Tot Ham
$P(Y)$	(prior)	0.33333	0.66666	-1.1	-0.4
$P(W_1 Y)$					
$P(W_2 Y)$					
	⋮				

$$P(\text{spam} \mid w) = 0.989$$

Training and Testing

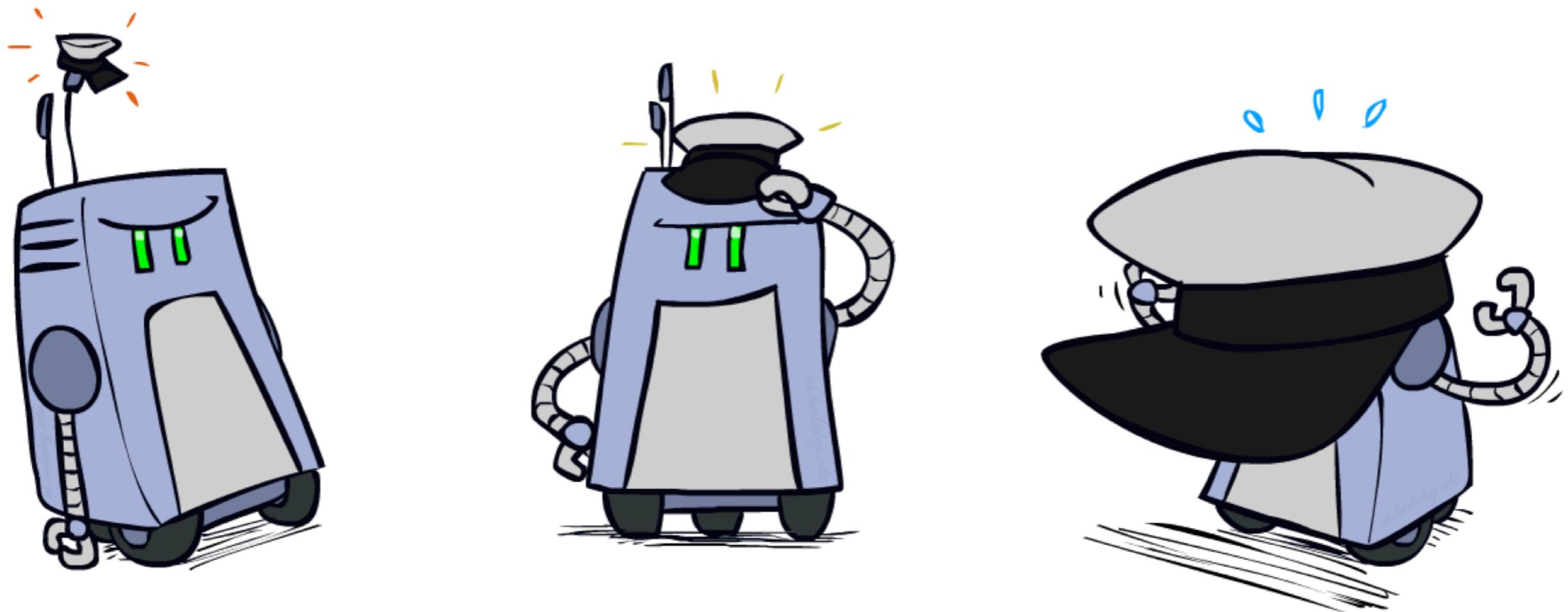


Important Concepts

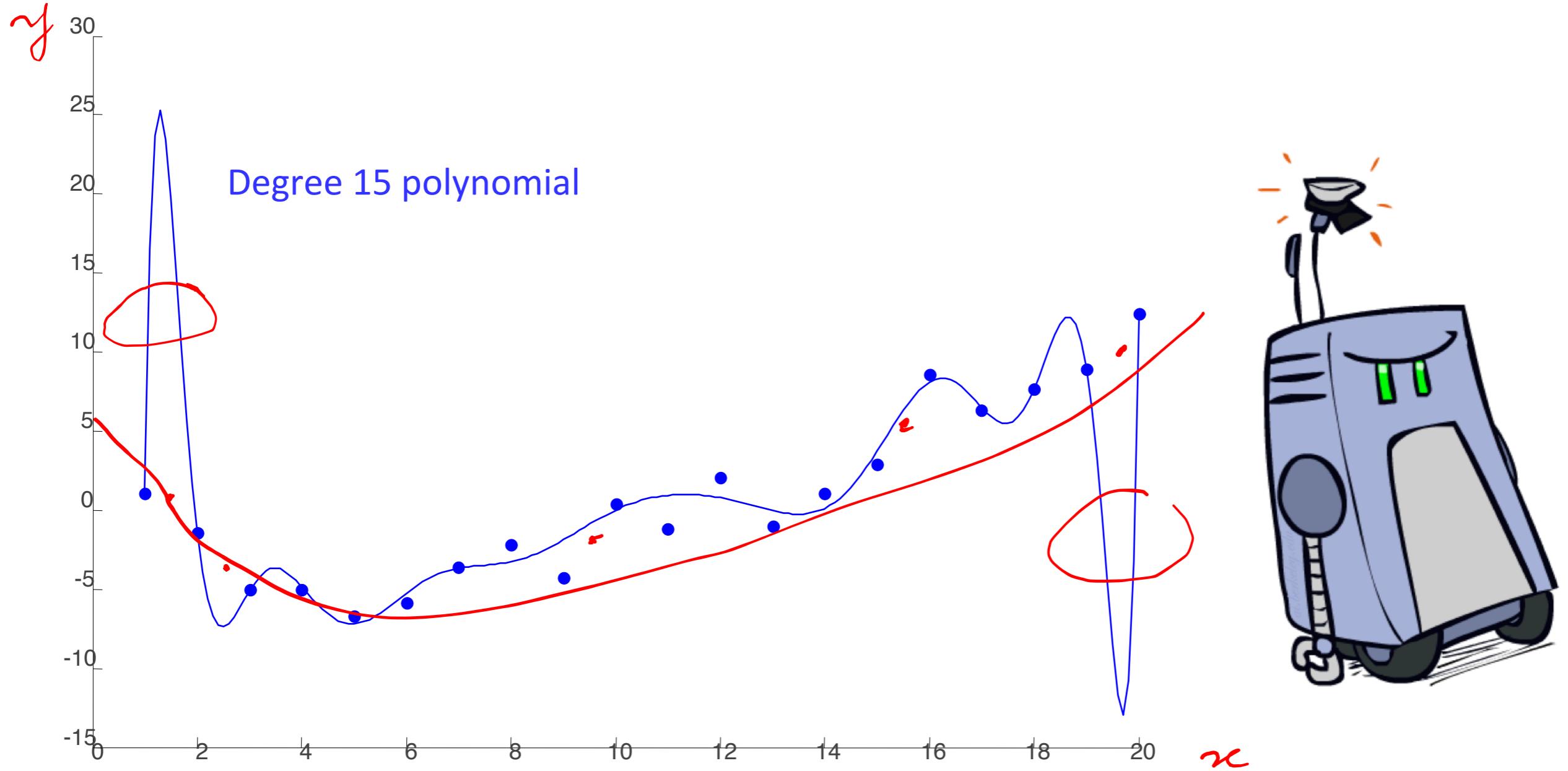
- ❖ **Data:** labeled instances, e.g., emails marked spam/ham
 - ❖ Training set ✓
 - ❖ Validation set ✓
 - ❖ Test set ✓
- ❖ **Features:** attribute-value pairs which characterize each x
- ❖ **Experimentation cycle**
 - ❖ Learn parameters (e.g., model probabilities) on training set
 - ❖ (Tune hyperparameters on validation set)
 - ❖ Compute accuracy of test set
 - ❖ **Very important:** never “peek” at the test set! ✓
- ❖ **Evaluation**
 - ❖ **Accuracy:** fraction of instances predicted correctly
- ❖ **Overfitting and generalization**
 - ❖ Want a classifier which does well on *test* data
 - ❖ **Overfitting:** fitting the training data very closely, but not generalizing well
 - ❖ **Underfitting:** fits the training set poorly



Underfitting and Overfitting



Overfitting



Example: Overfitting

$P(\text{features}, C = 2)$

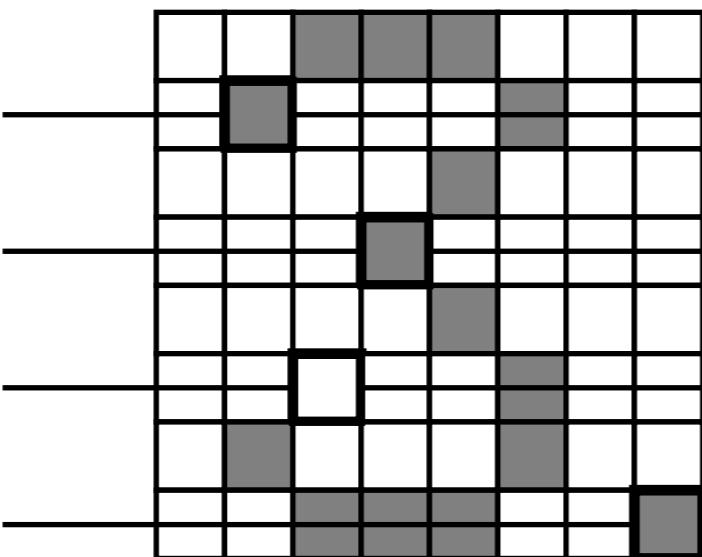
$$P(C = 2) = 0.1$$

$$P(\text{on}|C = 2) = 0.8$$

$$P(\text{on}|C = 2) = 0.1$$

$$P(\text{off}|C = 2) = 0.1$$

$$P(\text{on}|C = 2) = 0.01$$



$P(\text{features}, C = 3)$

$$P(C = 3) = 0.1$$

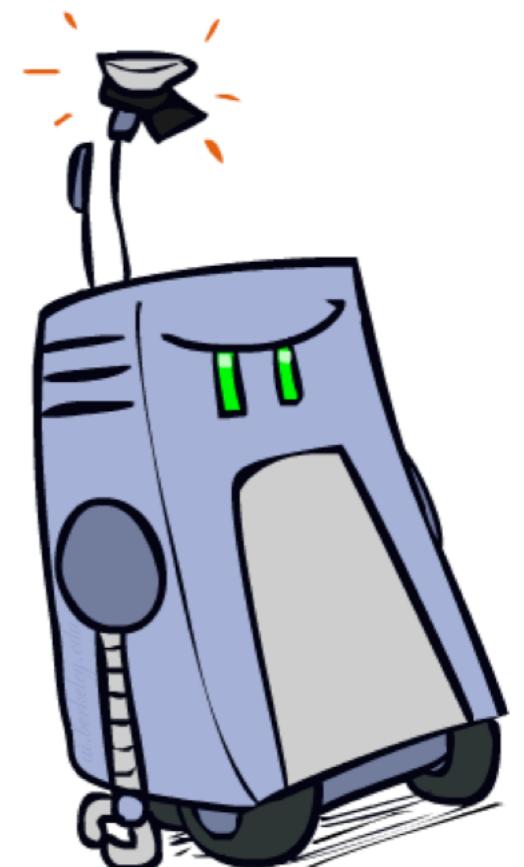
$$P(\text{on}|C = 3) = 0.8$$

$$P(\text{on}|C = 3) = 0.9$$

$$P(\text{off}|C = 3) = 0.7$$

$$P(\text{on}|C = 3) = 0.0$$

2 wins!!



Example: Overfitting

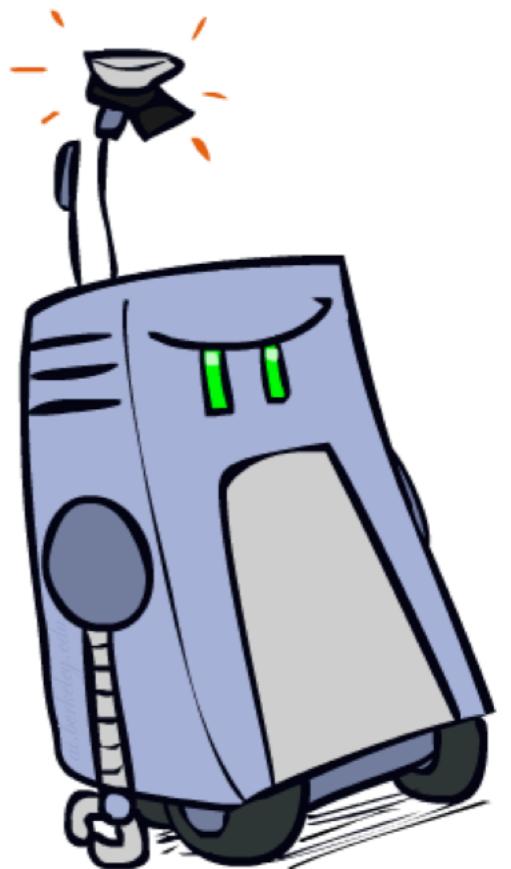
- ❖ Posteriors determined by *relative* probabilities (odds ratios):

$$\frac{P(W|\text{ham})}{P(W|\text{spam})}$$

south-west	:	inf
nation	:	inf
morally	:	inf
nicely	:	inf
extent	:	inf
seriously	:	inf
...		

$$\frac{P(W|\text{spam})}{P(W|\text{ham})}$$

screens	:	inf
minute	:	inf
guaranteed	:	inf
\$205.00	:	inf
delivery	:	inf
signature	:	inf
...		

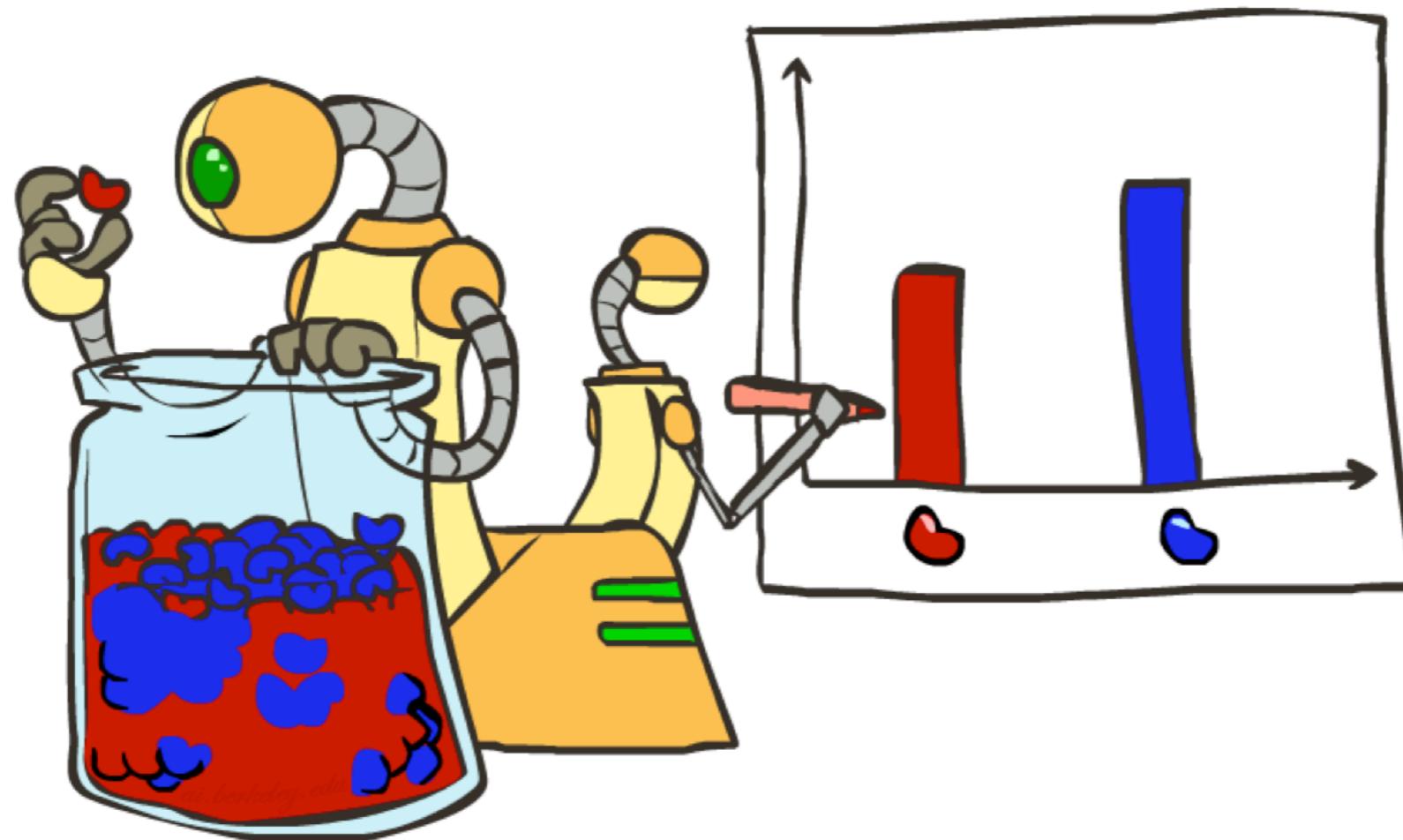


What went wrong here?

Generalization and Overfitting

- ❖ Relative frequency parameters will **overfit** the training data!
 - ❖ Just because we never saw a 3 with pixel (15,15) on during training doesn't mean we won't see it at test time
 - ❖ Unlikely that every occurrence of "minute" is 100% spam
 - ❖ Unlikely that every occurrence of "seriously" is 100% ham
 - ❖ What about all the words that don't occur in the training set at all?
 - ❖ In general, we can't go around giving unseen events zero probability
- ❖ As an extreme case, imagine using the entire email as the only feature
 - ❖ Would get the training data perfect (if deterministic labeling)
 - ❖ Wouldn't *generalize* at all
 - ❖ Just making the bag-of-words assumption gives us some generalization, but isn't enough
- ❖ To generalize better: we need to **smooth** or **regularize** the estimates

Parameter Estimation



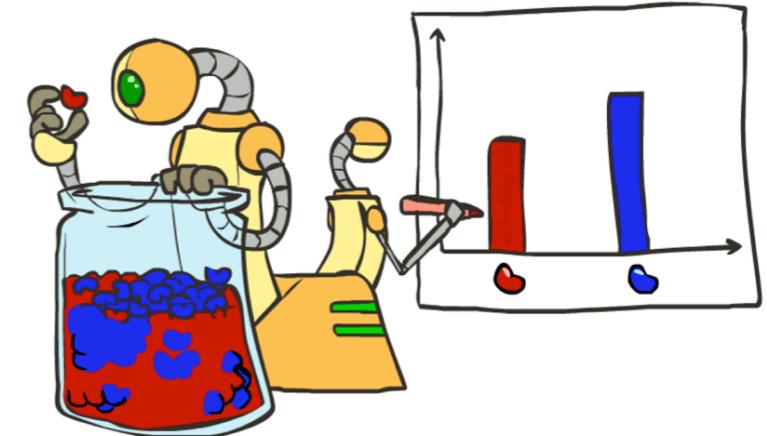
Parameter Estimation

- ❖ Estimating the distribution of a random variable
- ❖ *Elicitation*: ask a human (why is this hard?) ✓
- ❖ *Empirically*: use training data (learning!)
 - ❖ E.g.: for each outcome x , look at the *empirical rate* of that value:

$$P_{\text{ML}}(x) = \frac{\text{count}(x)}{\text{total samples}} \quad \checkmark$$

r r b

$$P_{\text{ML}}(\text{r}) = 2/3$$



- ❖ This is the estimate that maximizes the *likelihood of the data*

$$\underline{L}(\underline{x}, \theta) = \prod_i P_\theta(x_i) = \underline{\theta \cdot \theta \cdot (1 - \theta)}$$

$P(\mathcal{D} | \theta)$

$$P_\theta(x = \text{red}) = \theta$$

$$P_\theta(x = \text{blue}) = 1 - \theta$$

i.i.d
↑ identically distributed
independent

Maximum Likelihood Estimation

- ❖ **Data:** Observed set \mathcal{D} of α_H Head and α_T Tail
- ❖ **Hypothesis space:** Binomial distributions $\text{Bin}(\theta, \underbrace{\alpha_H + \alpha_T}_{\leftarrow})$
- ❖ **Learning:** finding θ is an optimization problem
 - ❖ What's the objective function?

$$P(\mathcal{D} | \theta) = \theta^{\alpha_H} (1 - \theta)^{\alpha_T}$$

- ❖ **MLE:** Choose θ to maximize probability of \mathcal{D}

$$\begin{aligned}\hat{\theta} &= \arg \max_{\theta} P(\mathcal{D} | \theta) \\ &= \arg \max_{\theta} \ln P(\mathcal{D} | \theta)\end{aligned}$$

Maximum Likelihood Estimation

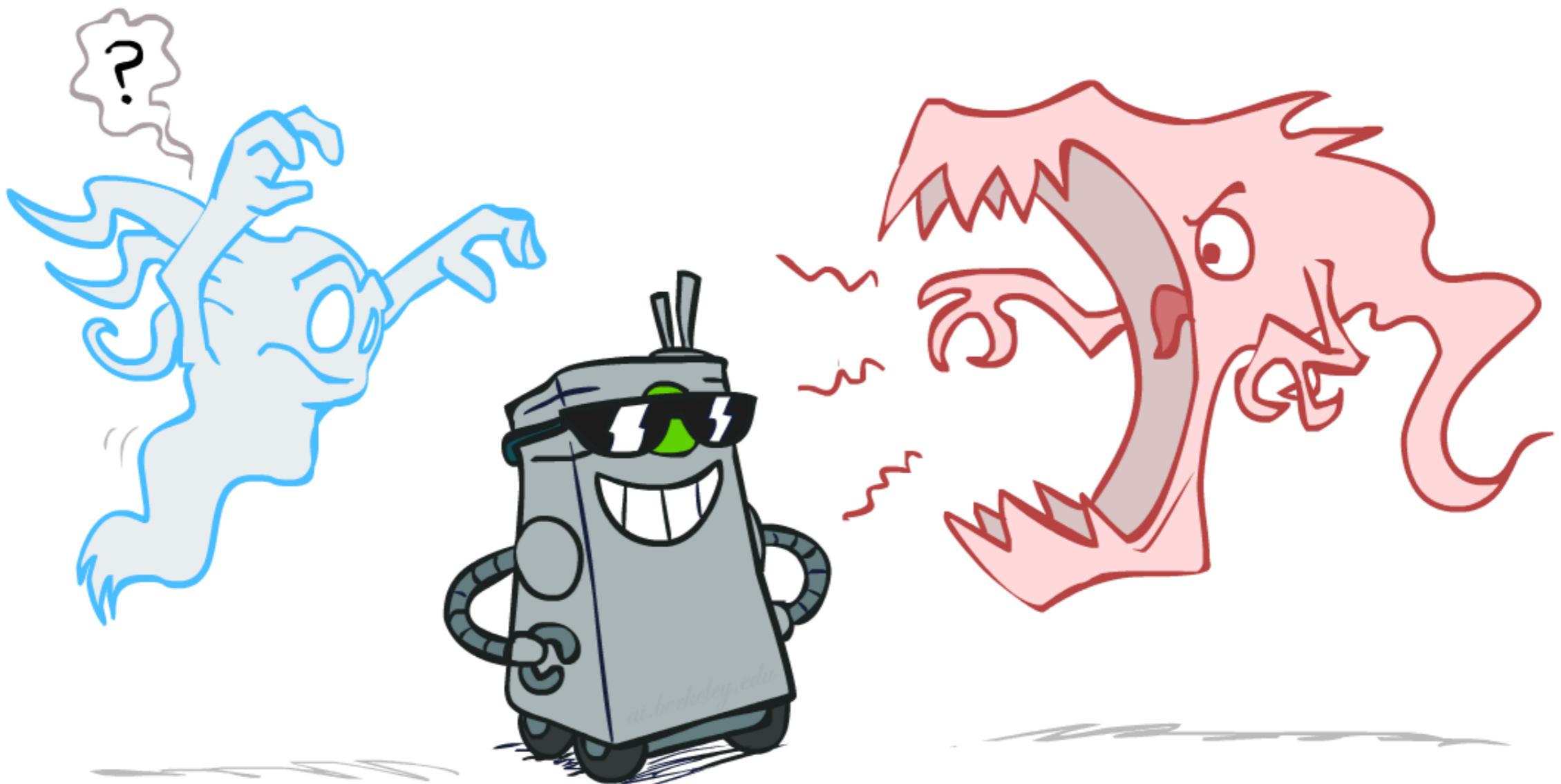
$$\begin{aligned}\hat{\theta} &= \arg \max_{\theta} (\ln P(\mathcal{D} | \theta)) \\ &= \arg \max_{\theta} \ln \theta^{\alpha_H} (1 - \theta)^{\alpha_T}\end{aligned}$$

- ❖ Set derivative to zero, and solve!

$$\begin{aligned}\frac{d}{d\theta} \ln P(\mathcal{D} | \theta) &= \frac{d}{d\theta} [\ln \theta^{\alpha_H} (1 - \theta)^{\alpha_T}] \\ &= \frac{d}{d\theta} [\alpha_H \ln \theta + \alpha_T \ln(1 - \theta)] \\ &= \alpha_H \frac{d}{d\theta} \ln \theta + \alpha_T \frac{d}{d\theta} \ln(1 - \theta) \\ &= \frac{\alpha_H}{\theta} - \frac{\alpha_T}{1 - \theta} = 0\end{aligned}$$

$$\boxed{\hat{\theta}_{MLE} = \frac{\alpha_H}{\alpha_H + \alpha_T}}$$

Smoothing



Maximum Likelihood?

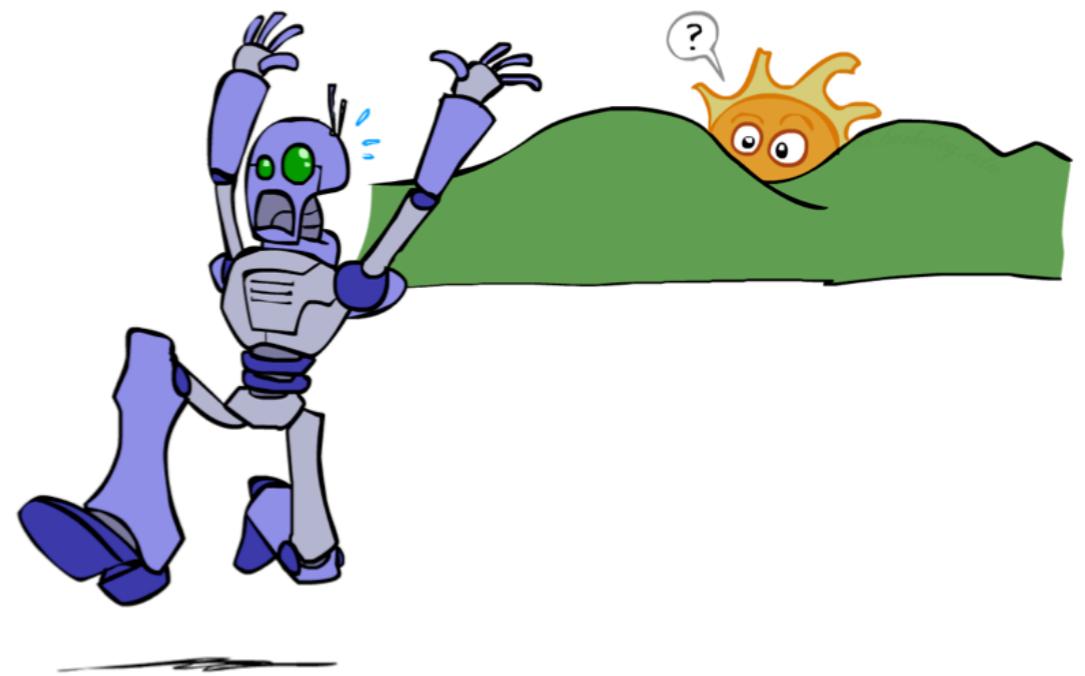
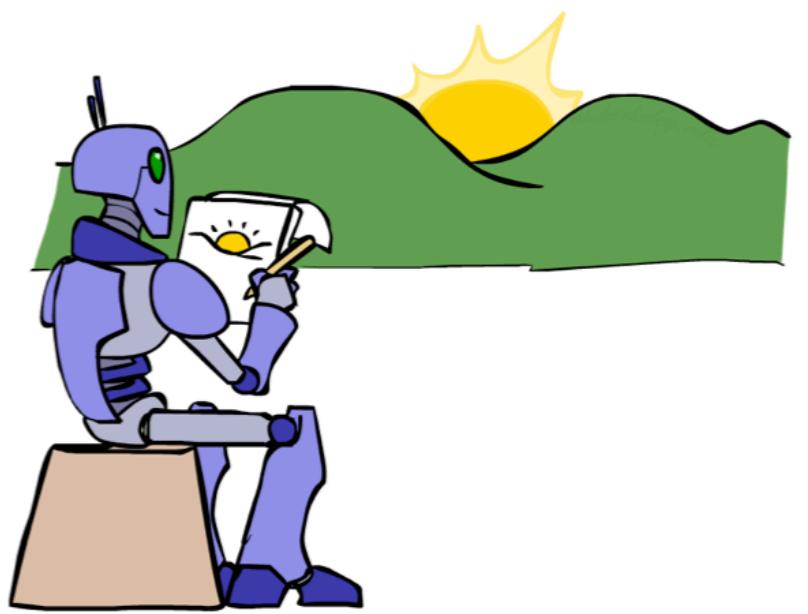
- ❖ Relative frequencies are the maximum likelihood estimates

$$\begin{aligned}\theta_{ML} &= \arg \max_{\theta} P(\mathbf{X}|\theta) \\ &= \arg \max_{\theta} \prod_i P_{\theta}(X_i)\end{aligned}\quad \Rightarrow \quad P_{ML}(x) = \frac{\text{count}(x)}{\text{total samples}}$$

- ❖ Another option is to consider the most likely parameter value given the data

$$\begin{aligned}\theta_{MAP} &= \arg \max_{\theta} P(\underline{\theta} | \mathbf{X}) \\ &= \arg \max_{\theta} P(\mathbf{X} | \theta) \underline{P(\theta) / P(\mathbf{X})} \quad \Rightarrow \quad \text{????} \\ &= \arg \max_{\theta} P(\mathbf{X} | \theta) \underline{P(\theta)} \quad \uparrow\end{aligned}$$

Unseen Events



Laplace Smoothing

- ❖ Laplace's estimate:

- ❖ Pretend you saw every outcome once more than you actually did

$$P_{LAP}(x) = \frac{c(x) + 1}{\sum_x [c(x) + 1]}$$
$$= \frac{c(x) + 1}{N + |X|}$$



$$P_{ML}(X) =$$

- ❖ Can derive this estimate with
Dirichlet Priors

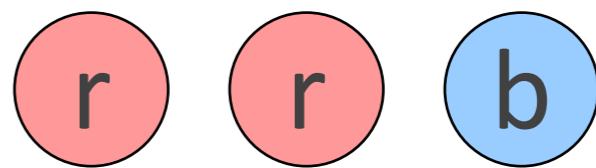
$$P_{LAP}(X) =$$

Laplace Smoothing

❖ Laplace's estimate (extended):

- ❖ Pretend you saw every outcome k extra times

$$P_{LAP,k}(x) = \frac{c(x) + k}{N + k|X|}$$



- ❖ What's Laplace with $k = 0$?
- ❖ k is the **strength** of the prior

$$P_{LAP,0}(X) =$$

❖ Laplace for conditionals:

- ❖ Smooth each condition independently:

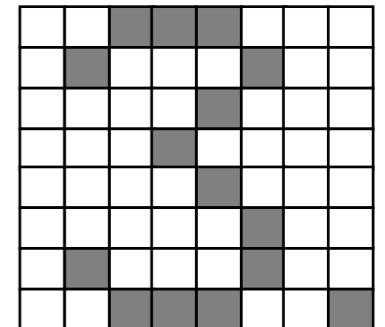
$$P_{LAP,k}(x|y) = \frac{\underline{c(x,y)} + k}{\underline{c(y)} + k|X|}$$

$$P_{LAP,1}(X) =$$

$$P_{LAP,100}(X) =$$

Estimation: Linear Interpolation*

- ❖ In practice, Laplace can perform poorly for $P(\underline{X} | Y)$:
 - ❖ When $|X|$ is very large
 - ❖ When $|Y|$ is very large
- ❖ Another option: linear interpolation
 - ❖ Also get the empirical $P(\underline{X})$ from the data
 - ❖ Make sure the estimate of $P(X | Y)$ isn't too different from the empirical $P(X)$



$$P_{LIN}(x|y) = \alpha \hat{P}(\underline{x}|y) + (1.0 - \alpha) \hat{P}(\underline{x})$$

- ❖ What if α is 0? 1?

Real NB: Smoothing

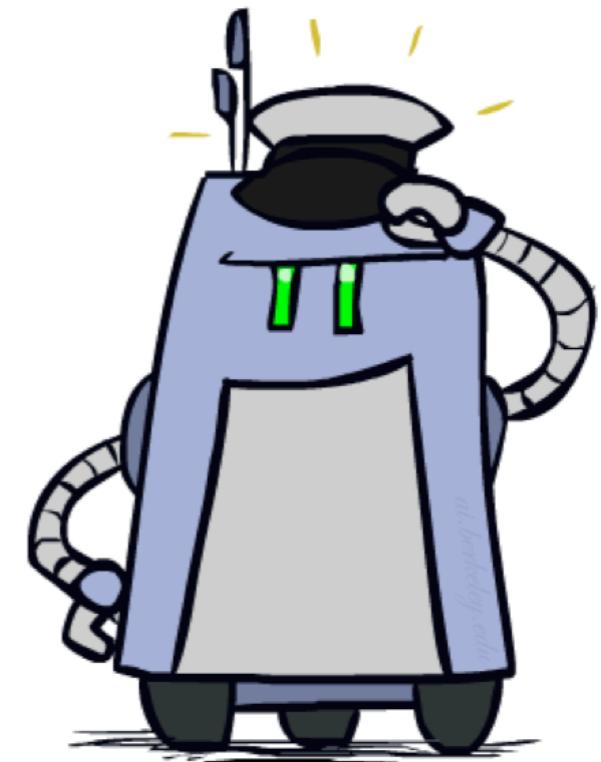
- ❖ For real classification problems, smoothing is critical
- ❖ New odds ratios:

$$\frac{P(W|\text{ham})}{P(W|\text{spam})}$$

helvetica	:	11.4
seems	:	10.8
group	:	10.2
ago	:	8.4
areas	:	8.3
...		

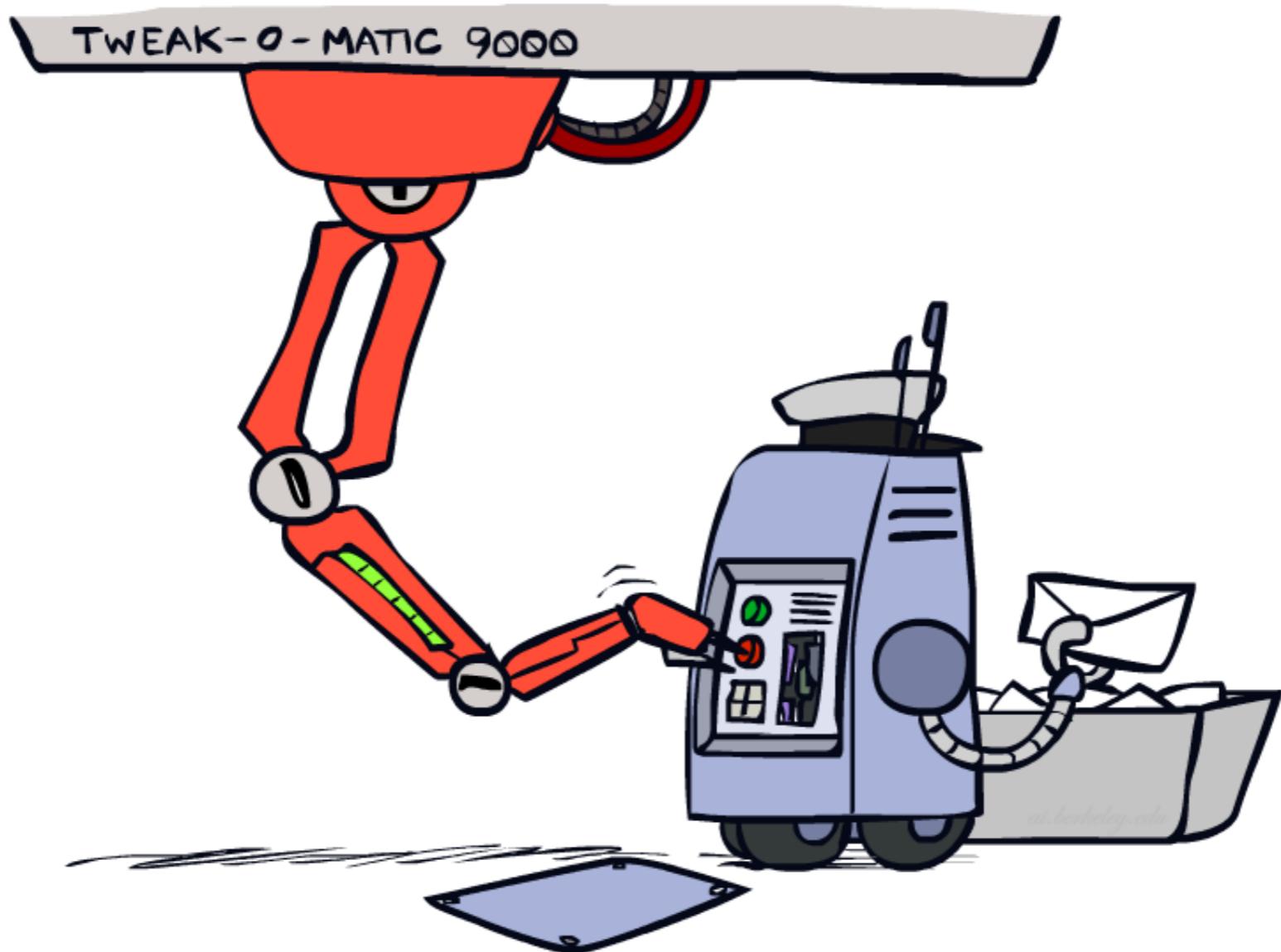
$$\frac{P(W|\text{spam})}{P(W|\text{ham})}$$

verdana	:	28.8
Credit	:	28.4
ORDER	:	27.2
	:	26.9
money	:	26.5
...		



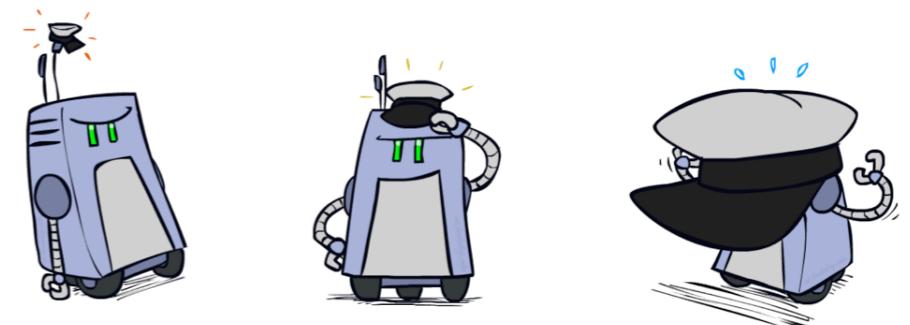
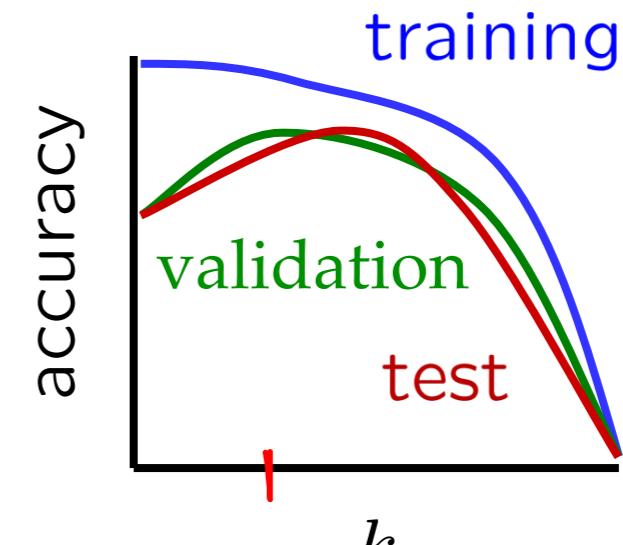
Do these make more sense?

Tuning

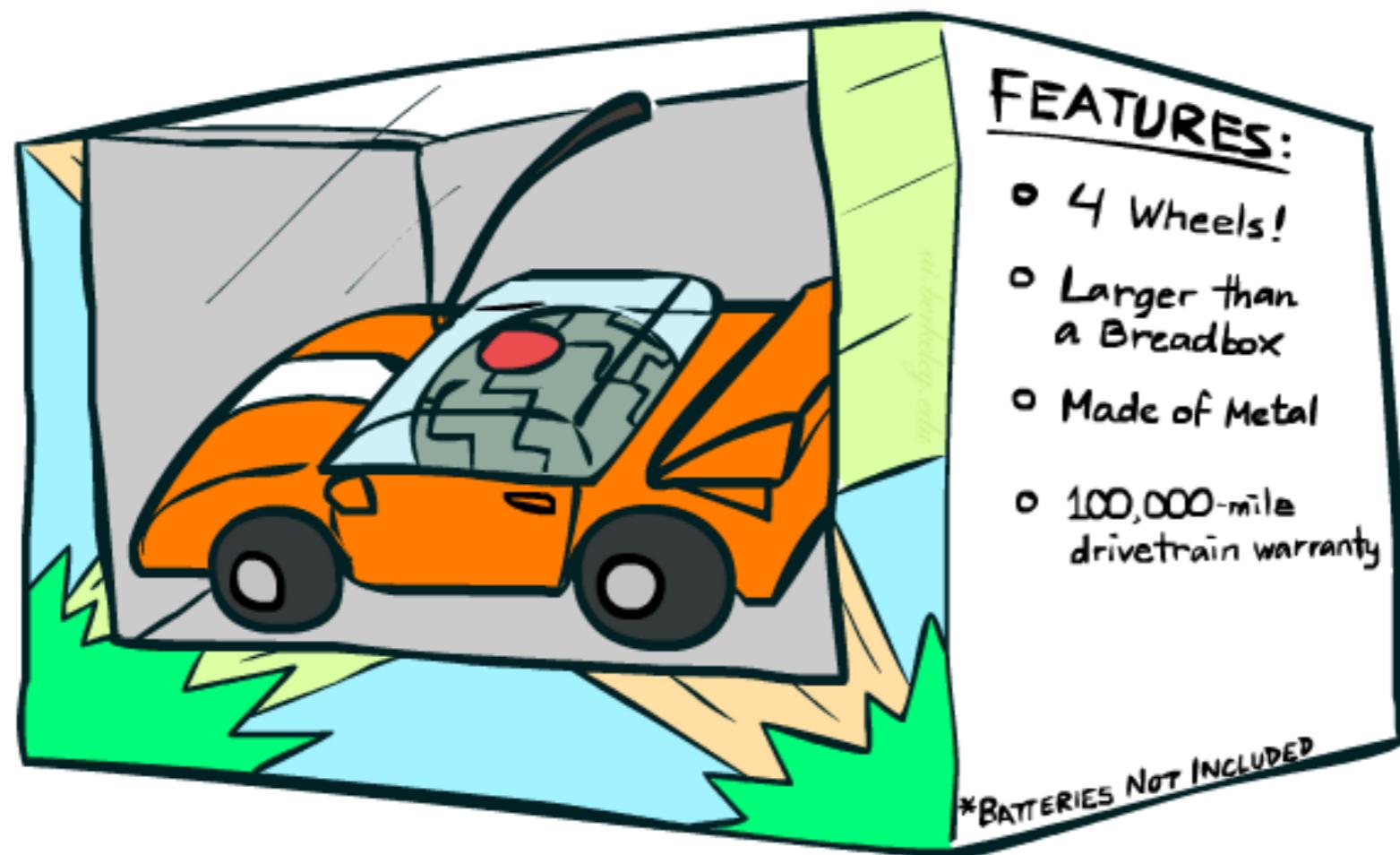


Tuning on Validation Data

- ❖ Now we've got two kinds of unknowns
 - ❖ Parameters: the probabilities $P(\underline{X} | \underline{Y})$, $P(\underline{Y})$
 - ❖ Hyperparameters: e.g., the amount / type of smoothing to do, \underline{k} , $\underline{\alpha}$
- ❖ What should we learn where?
 - ❖ Learn parameters from training data
 - ❖ Tune hyperparameters on different data
 - ❖ Why?
 - ❖ For each value of the hyperparameters, train and test on the validation data
 - ❖ Choose the best value and do a final test on the test data



Features



Errors, and What to Do

❖ Examples of errors

Dear GlobalSCAPE Customer,

GlobalSCAPE has partnered with ScanSoft to offer you the latest version of OmniPage Pro, for just \$99.99* - the regular list price is \$499! The most common question we've received about this offer is - Is this genuine? We would like to assure you that this offer is authorized by ScanSoft, is genuine and valid. You can get the . . .

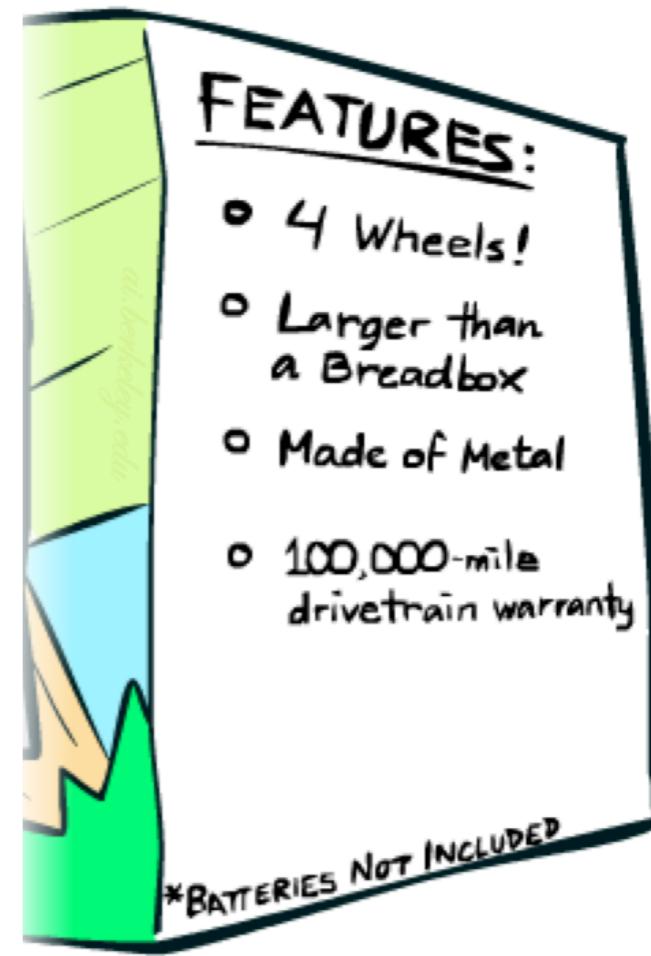
. . . To receive your \$30 Amazon.com promotional certificate, click through to

<http://www.amazon.com/apparel>

and see the prominent link for the \$30 offer. All details are there. We hope you enjoyed receiving this message. However, if you'd rather not receive future e-mails announcing new store launches, please click . . .

What to Do About Errors?

- ❖ Need more features— words aren't enough!
 - ❖ Have you emailed the sender before?
 - ❖ Have 1K other people just gotten the same email?
 - ❖ Is the sending information consistent?
 - ❖ Is the email in ALL CAPS?
 - ❖ Do inline URLs point where they say they point?
 - ❖ Does the email address you by (your) name?
- ❖ Can add these information sources as new variables in the NB model
- ❖ Next class we'll talk about classifiers which let you easily add arbitrary features more easily



Baselines

- ❖ First step: get a **baseline**
 - ❖ Baselines are very simple “straw man” procedures
 - ❖ Help determine how hard the task is
 - ❖ Help know what a “good” accuracy is
- ❖ Weak baseline: most frequent label classifier
 - ❖ Gives all test instances whatever label was most common in the training set
 - ❖ E.g. for spam filtering, might label everything as ham
 - ❖ Accuracy might be very high if the problem is skewed
 - ❖ E.g. calling everything “ham” gets 66%, so a classifier that gets 70% isn’t very good...
- ❖ For real research, usually use previous work as a (strong) baseline

Confidences from a Classifier

- ❖ The **confidence** of a probabilistic classifier:

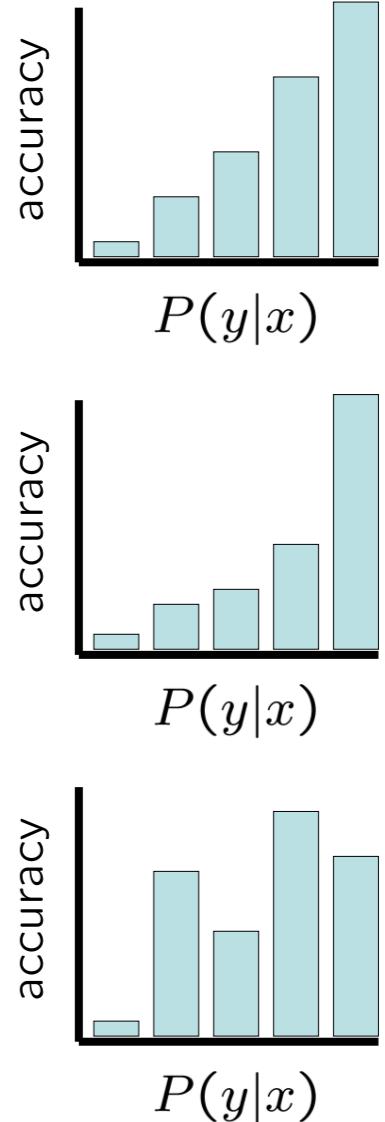
- ❖ Posterior over the top label

$$\text{confidence}(x) = \max_y P(y|x)$$

- ❖ Represents how sure the classifier is of the classification
- ❖ Any probabilistic model will have confidences
- ❖ No guarantee confidence is correct

- ❖ **Calibration**

- ❖ Weak calibration: higher confidences mean higher accuracy
- ❖ Strong calibration: confidence predicts accuracy rate
- ❖ What's the value of calibration?



Summary

- ❖ Bayes rule lets us do diagnostic queries with causal probabilities
- ❖ The naïve Bayes assumption takes all features to be independent given the class label
- ❖ We can build classifiers out of a naïve Bayes model using training data
- ❖ Smoothing estimates is important in real systems
- ❖ Classifier confidences are useful, when you can get them