# CSE 573 : Artificial Intelligence

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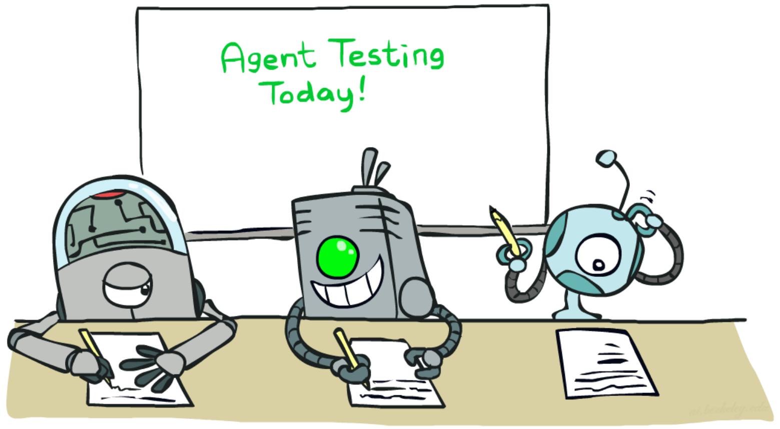
Machine Learning, Perceptrons

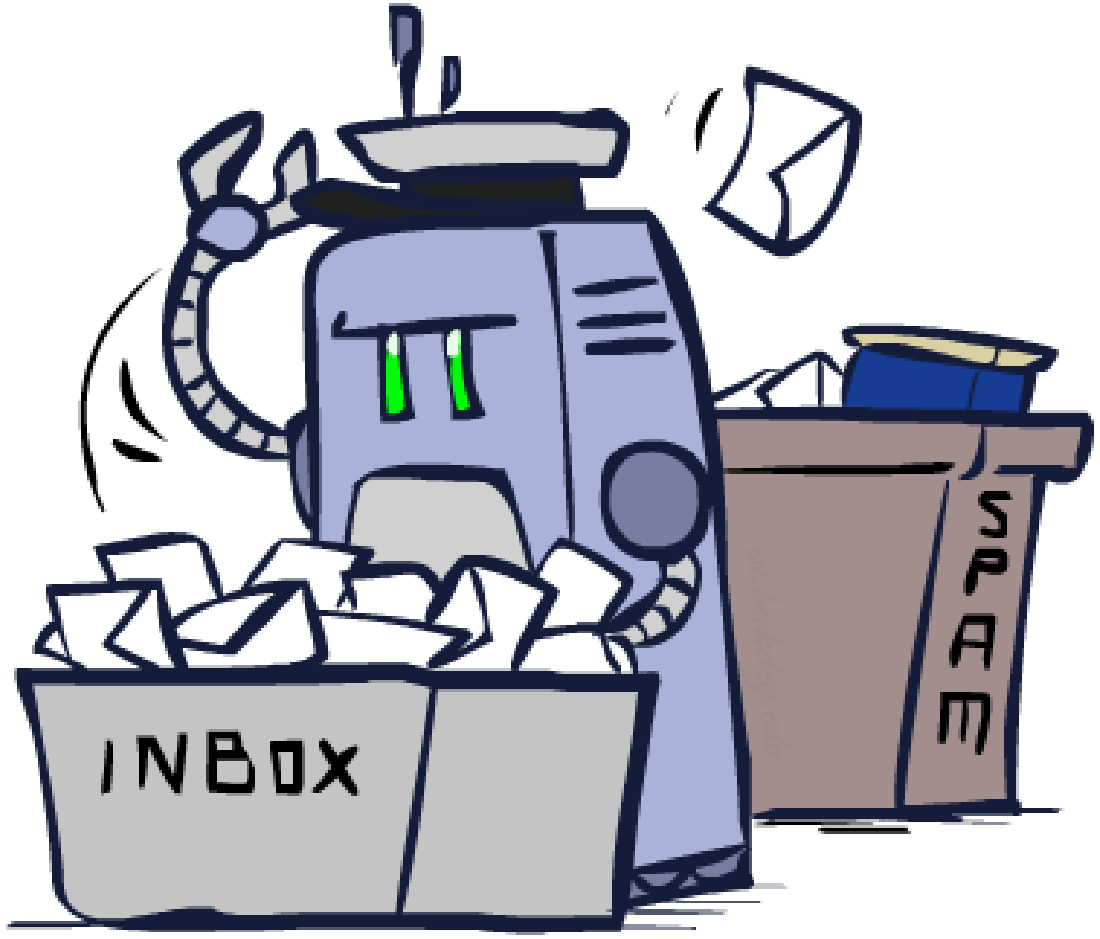
slides adapted from
Dan Klein, Pieter Abbeel ai.berkeley.edu
And Dan Weld, Luke Zettlemoyer



# 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. graphs)
  - Learning hidden concepts (e.g. clustering)
- First: model-based classification

# Classification



# Example: Spam Filter

- Input: an email
- Output: spam/ham

- 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, WidelyBroadcast
  - …

✗

> Dear Sir.
>
> First, I must solicit your confidence in this transaction, this is by virture of its nature as being utterly confidencial 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

✓

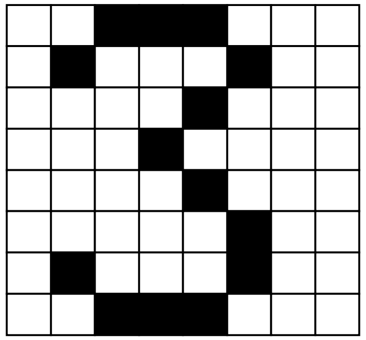
> Ok, Iknow this is blatantly OT but I'm beginning to go insane. Had an old Dell Dimension XPS sitting in the corner and decided to put it to use, I know it was working pre being stuck in the corner, but when I plugged it in, hit the power nothing happened.

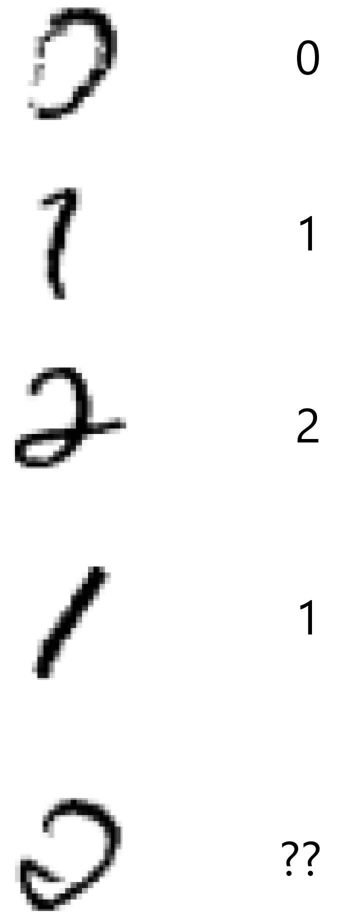
# Example: Digit Recognition

- 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
  - …

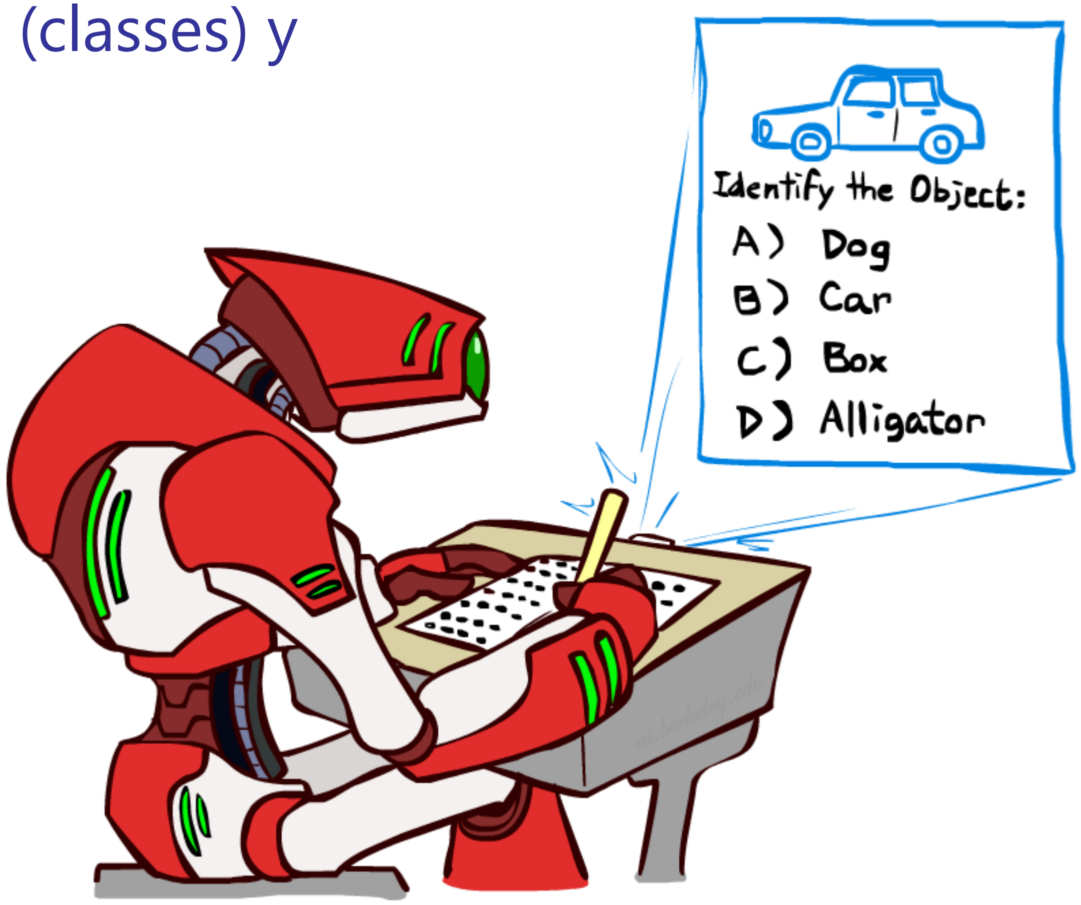




# Other Classification Tasks

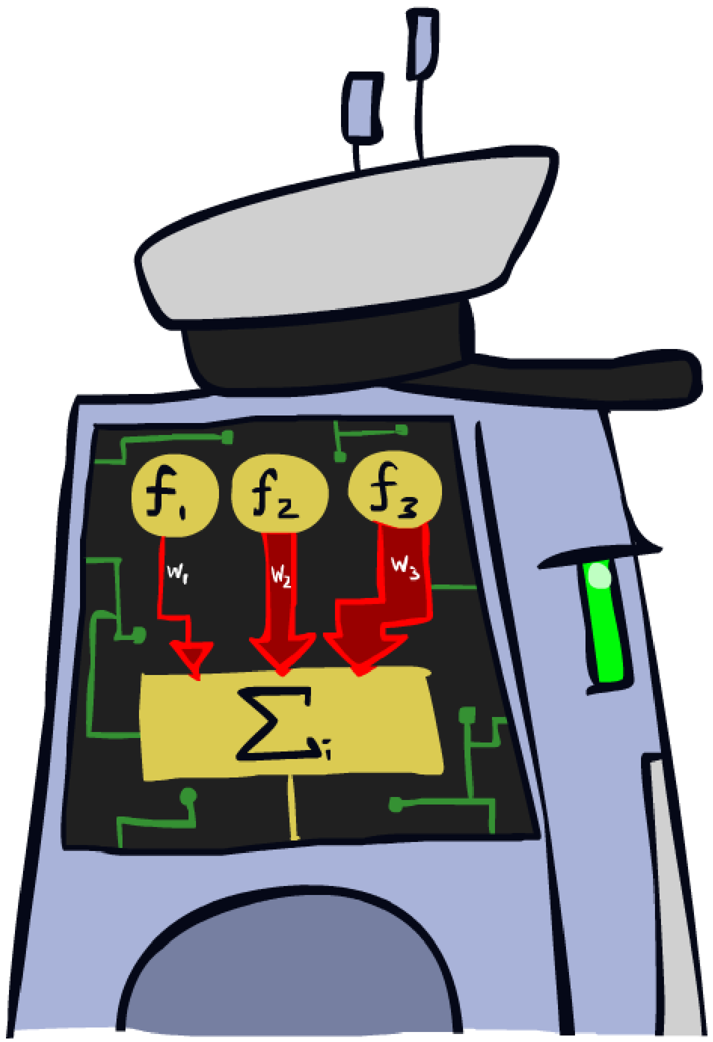
- Classification: given inputs x, predict labels (classes) y

- 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!

## Linear Classifiers



# A Spam Filter

- Data:
  - Collection of emails, labeled spam or ham
  - Note: someone has to hand label all this data!
  - Split into training, held-out, test sets
- Classifiers
  - Learn on the training set
  - (Tune it on a held-out set)
  - Test it on new emails

✗

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# Feature Vectors

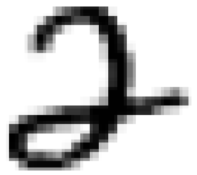
$x$ $\rightarrow$ $f(x)$ $\rightarrow$ $y$

```
Hello,

Do you want free printr
cartriges?  Why pay more
when you can get them
ABSOLUTELY FREE!  Just
```

```
# free       : 2
YOUR_NAME    : 0
MISSPELLED   : 2
FROM_FRIEND  : 0
...
```

SPAM
or
+

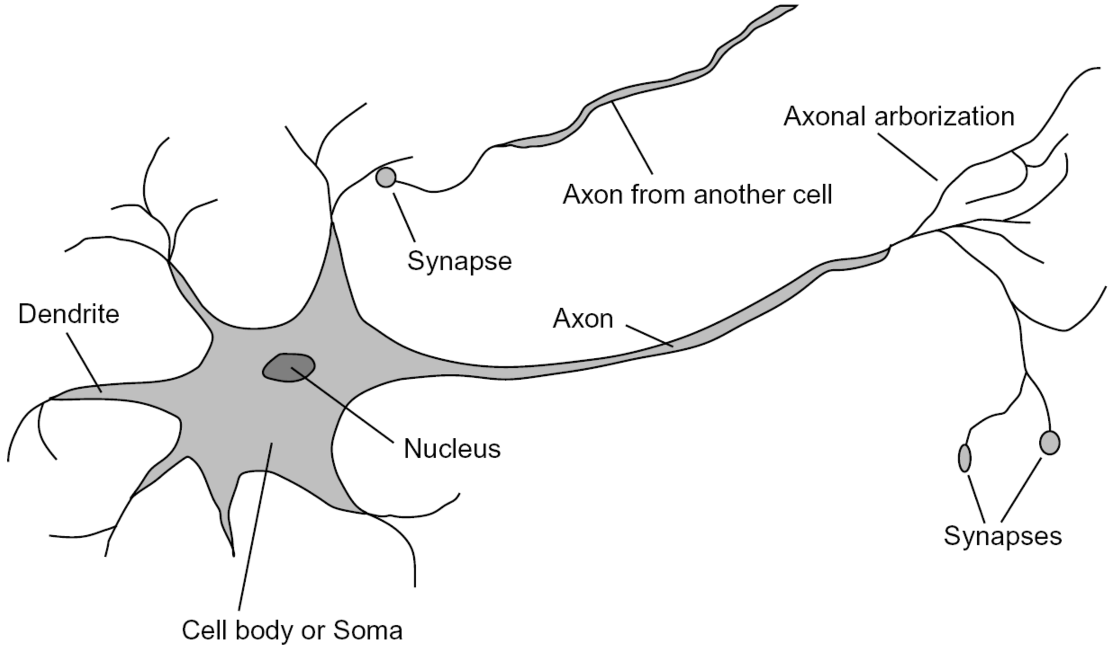


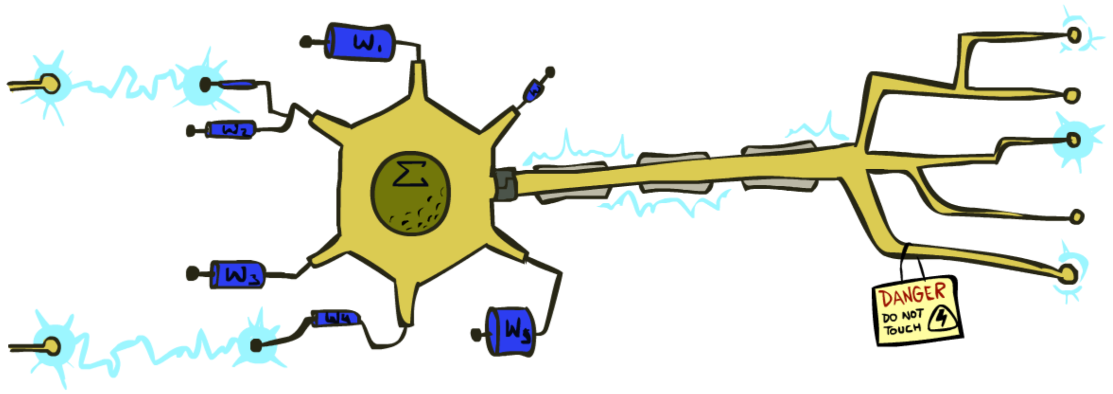
```
PIXEL-7,12   : 1
PIXEL-7,13   : 0
...
NUM_LOOPS    : 1
...
```

“2”

# Some (Simplified) Biology

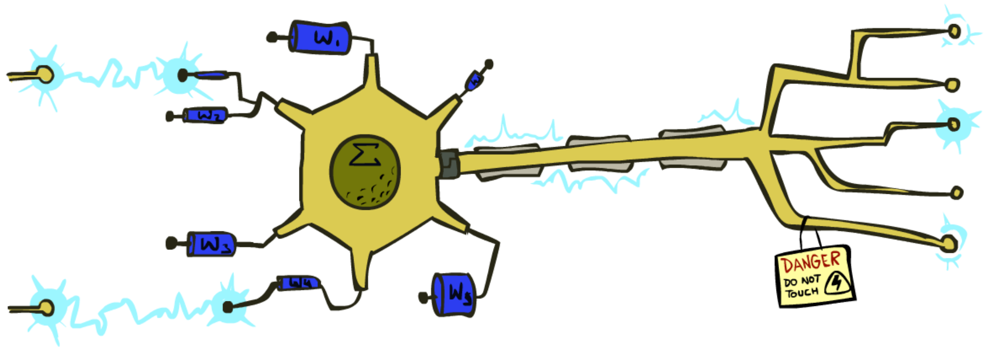
- Very loose inspiration: human neurons





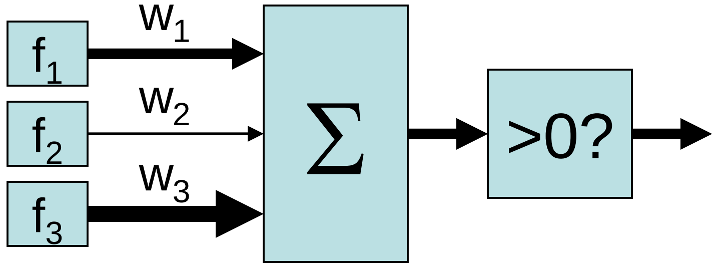
# Linear Classifiers

- Inputs are feature values
- Each feature has a weight
- Sum is the activation



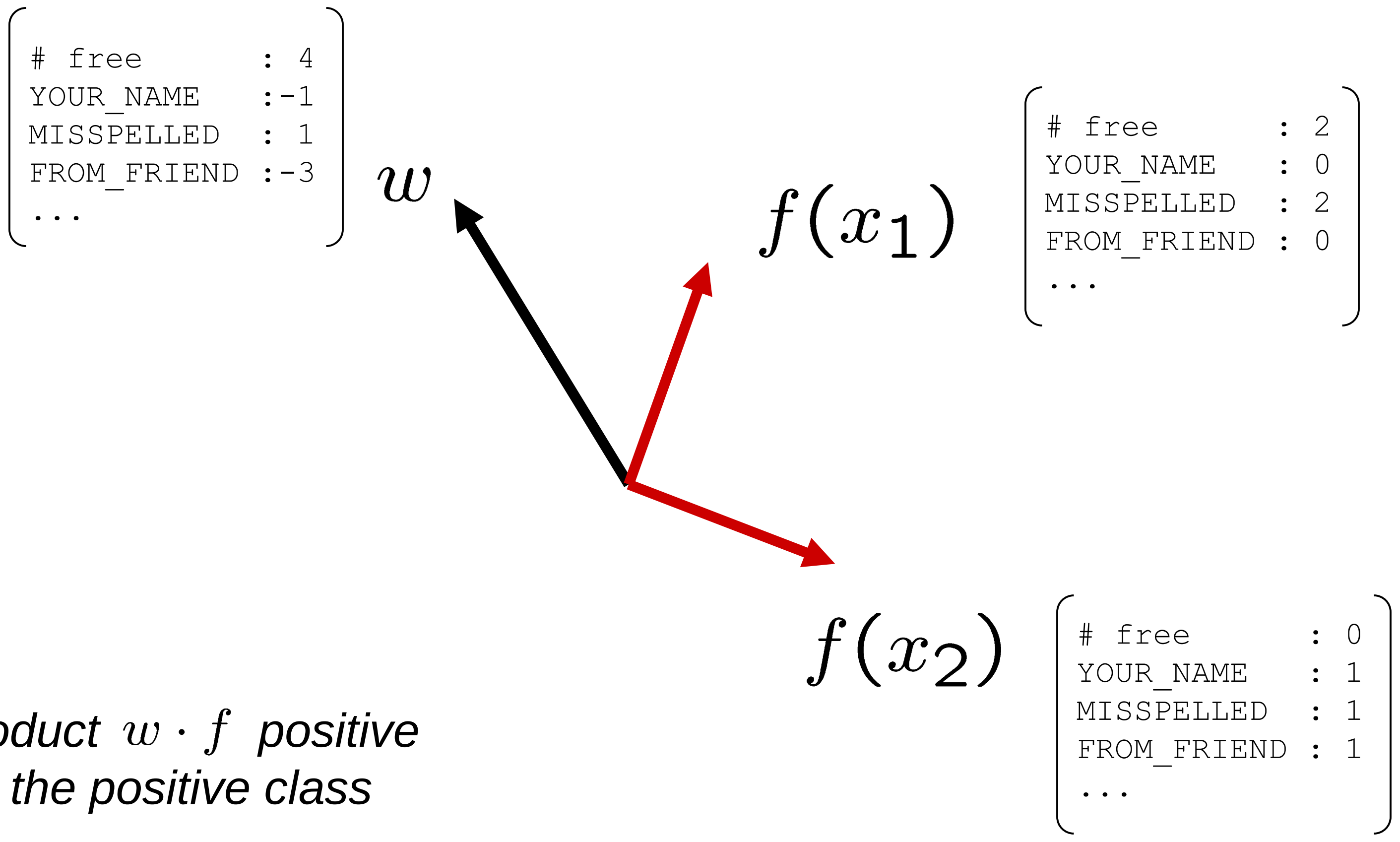
$$\text{activation}_w(x) = \sum_i w_i \cdot f_i(x) = w \cdot f(x)$$

- If the activation is:
  - Positive, output +1
  - Negative, output -1



# Weights

- Binary case: compare features to a weight vector
- Learning: figure out the weight vector from examples



```
# free       : 4
YOUR_NAME    :-1
MISSPELLED   : 1
FROM_FRIEND  :-3
...
```

$w$

$f(x_1)$

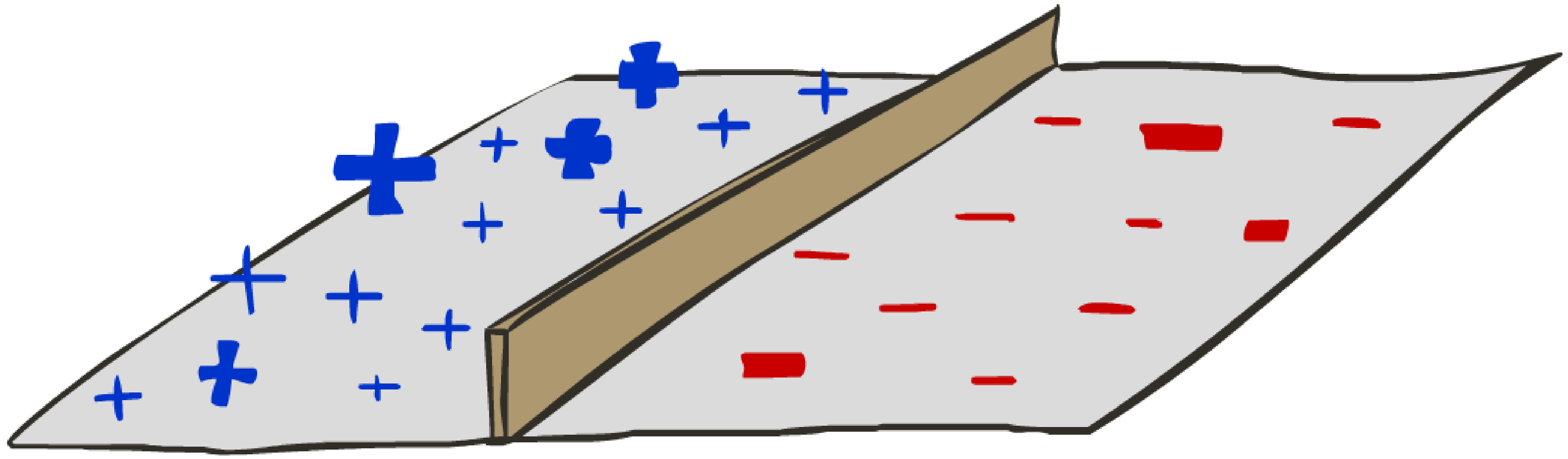
```
# free       : 2
YOUR_NAME    : 0
MISSPELLED   : 2
FROM_FRIEND  : 0
...
```

$f(x_2)$

```
# free       : 0
YOUR_NAME    : 1
MISSPELLED   : 1
FROM_FRIEND  : 1
...
```

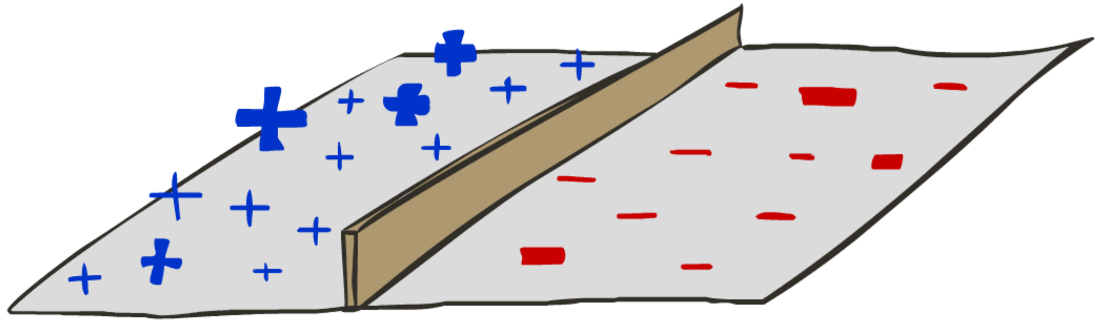
*Dot product* $w \cdot f$ *positive means the positive class*

# Decision Rules



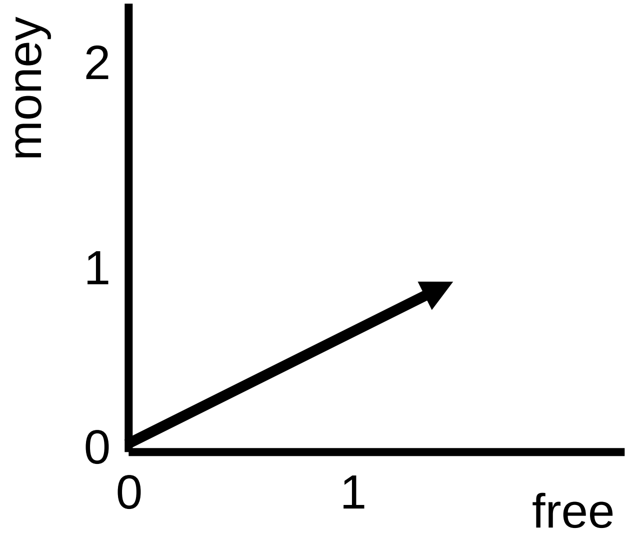
# Binary Decision Rule

- In the space of feature vectors
  - Examples are points
  - Any weight vector is a hyperplane
  - One side corresponds to Y=+1
  - Other corresponds to Y=-1



$w$

```
BIAS  : -3
free  :  4
money :  2
...
```



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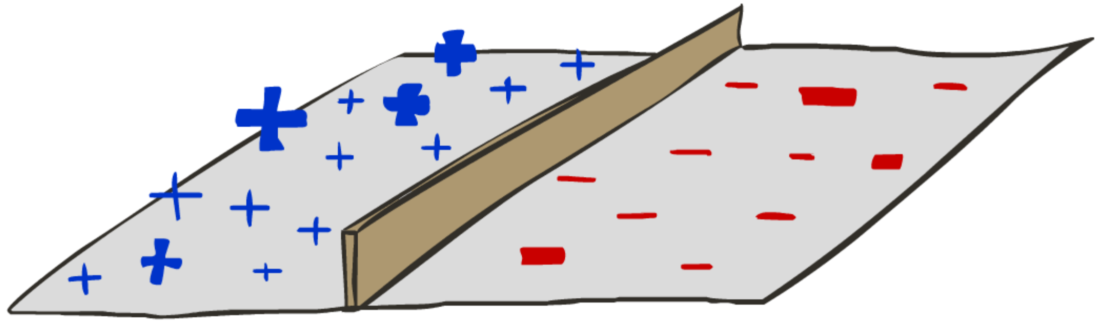
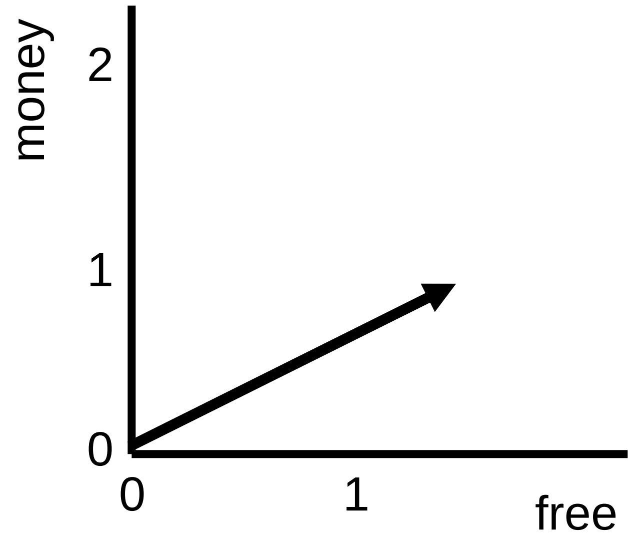
$w$

```
free  :  4
money :  2
```





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  - Any weight vector is a hyperplane
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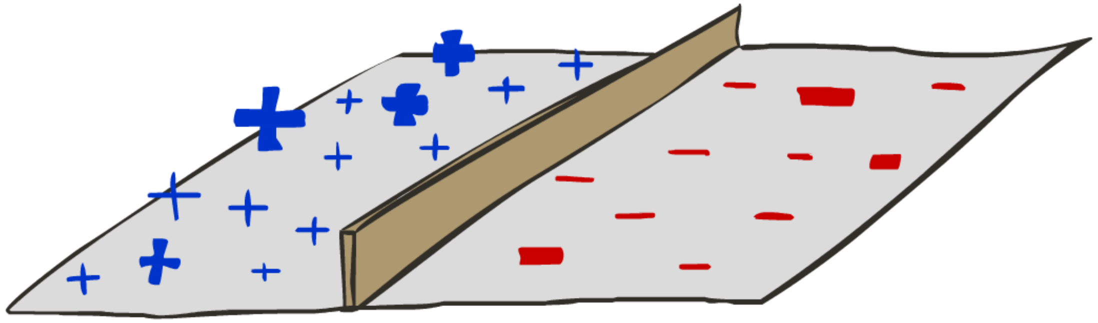
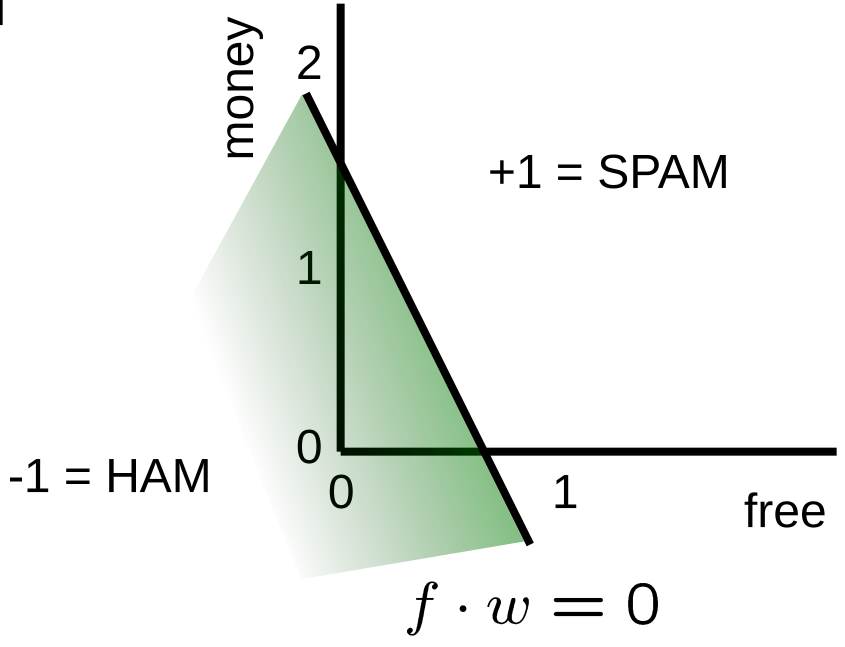
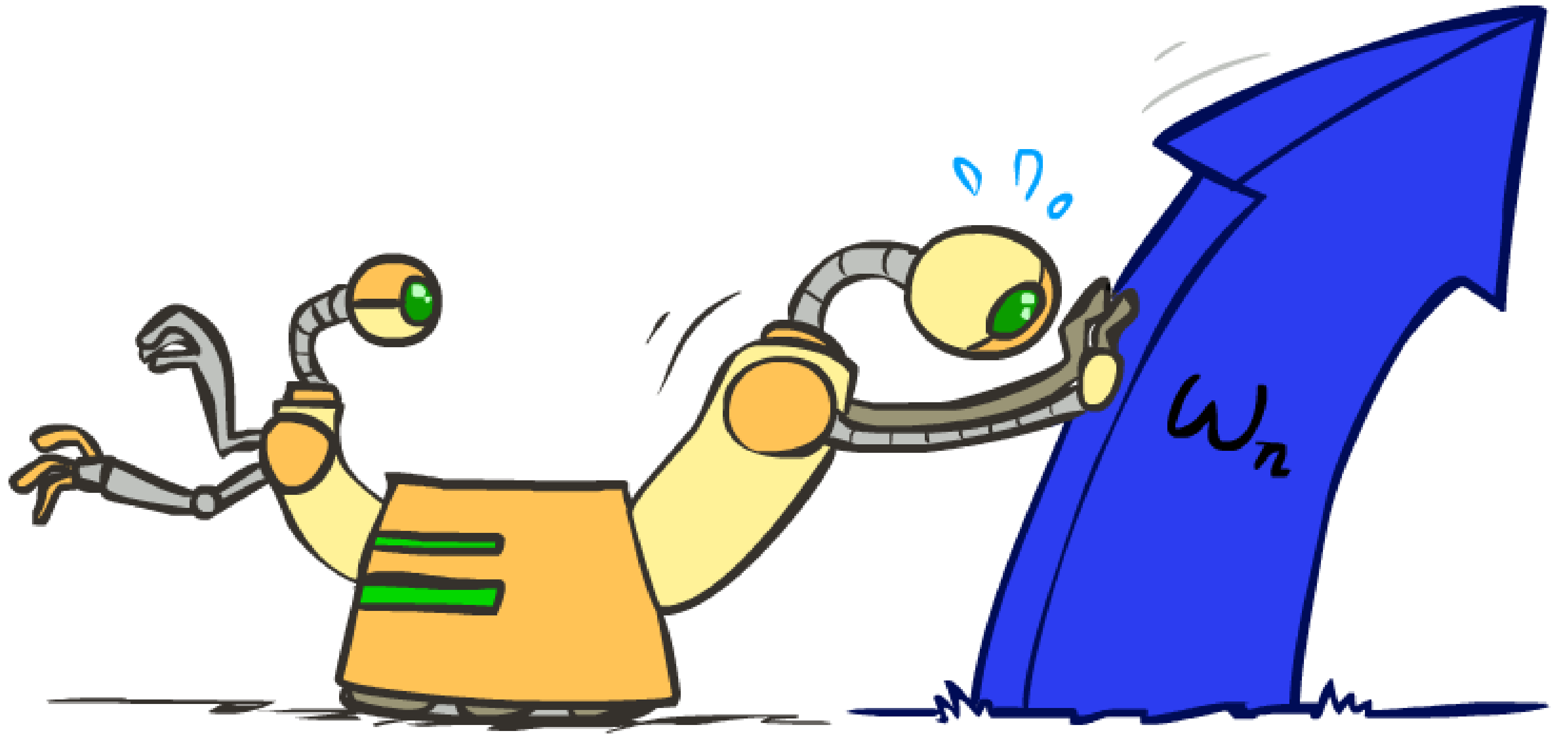


$w$

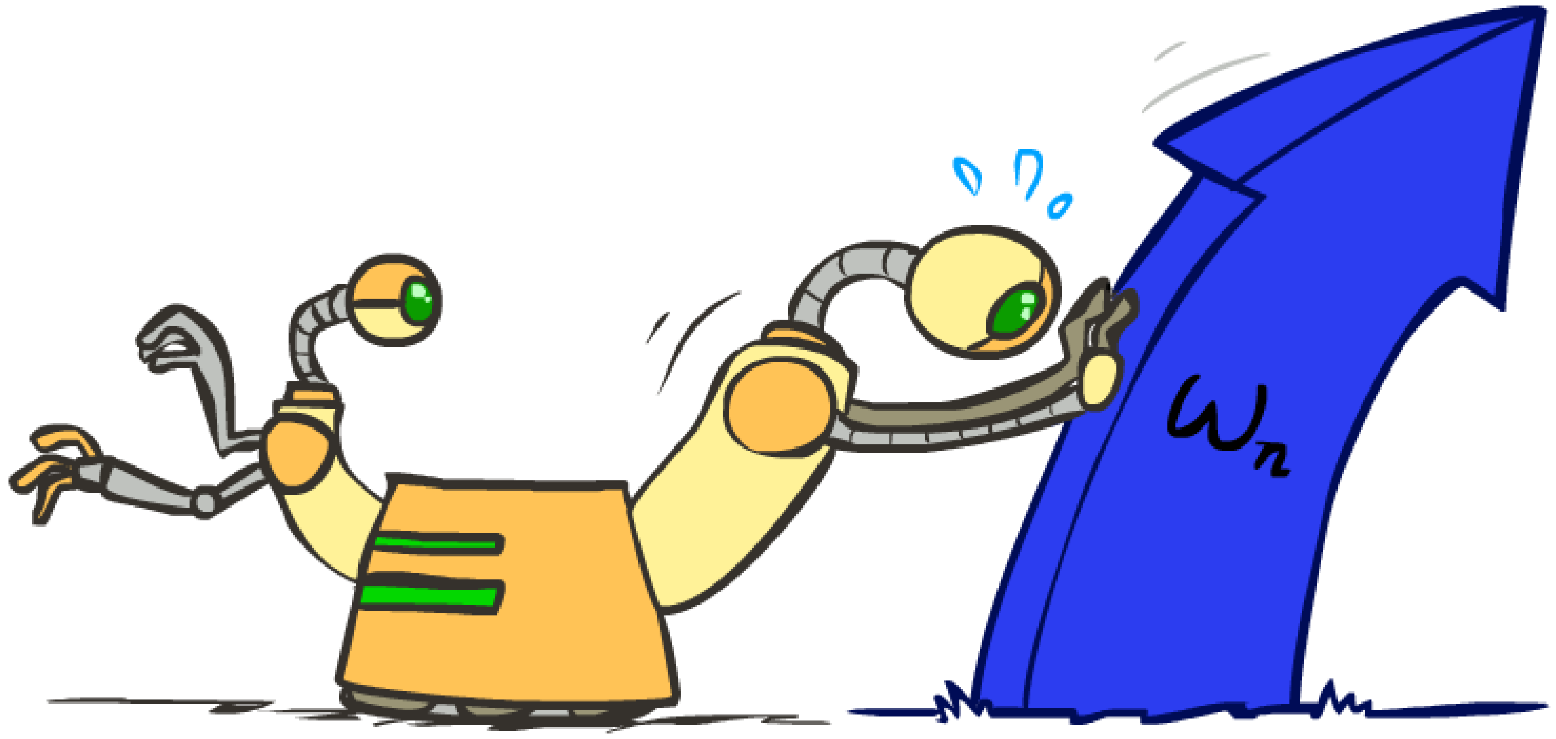
```
BIAS  : -3
free  :  4
money :  2
...
```



# How do we learn weight?

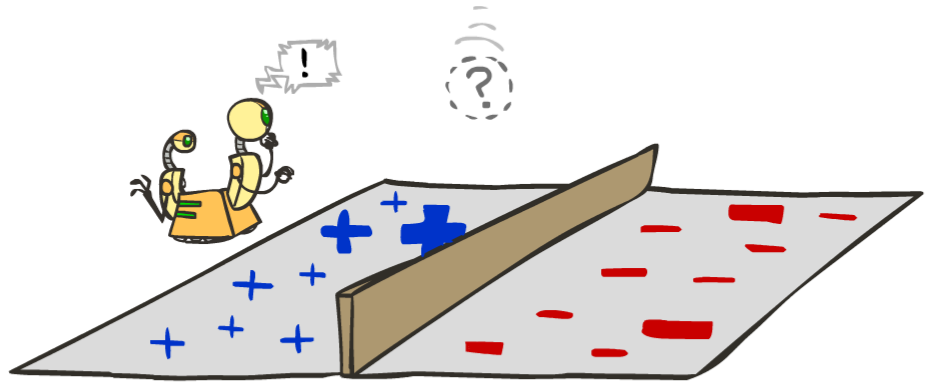


# Weight Updates

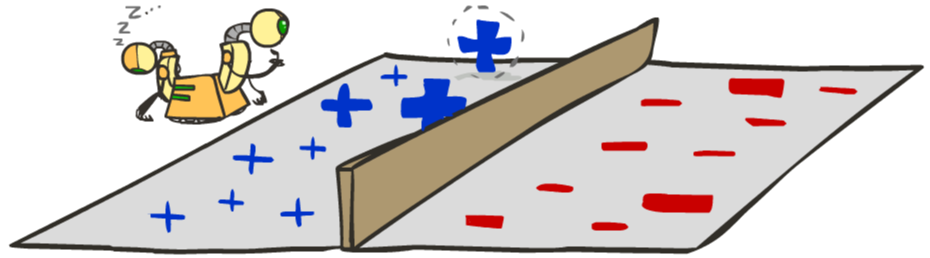


# Learning: Binary Perceptron

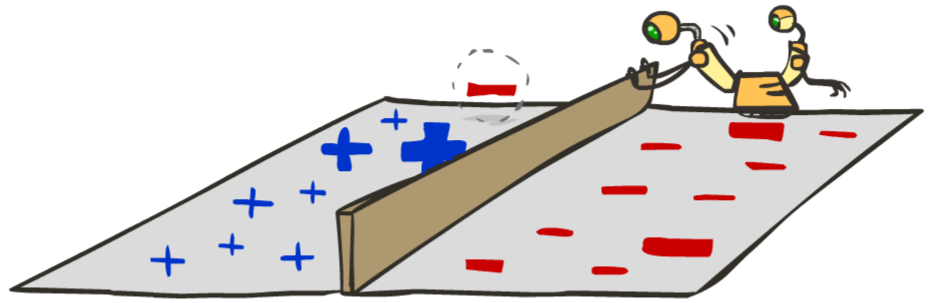
- Start with weights = 0
- For each training instance:
  - Classify with current weights



  - If correct (i.e., y=y*), no change!



  - If wrong: adjust the weight vector



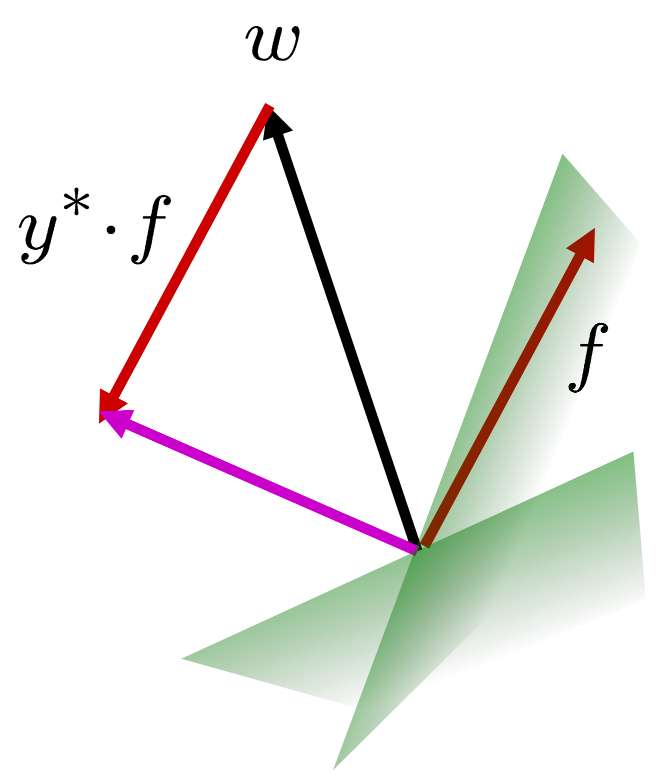
# Learning: Binary Perceptron

- Start with weights = 0
- For each training instance:
  - Classify with current weights

$$y = \begin{cases} +1 & \text{if } \; w \cdot f(x) \geq 0 \\ -1 & \text{if } \; w \cdot f(x) < 0 \end{cases}$$

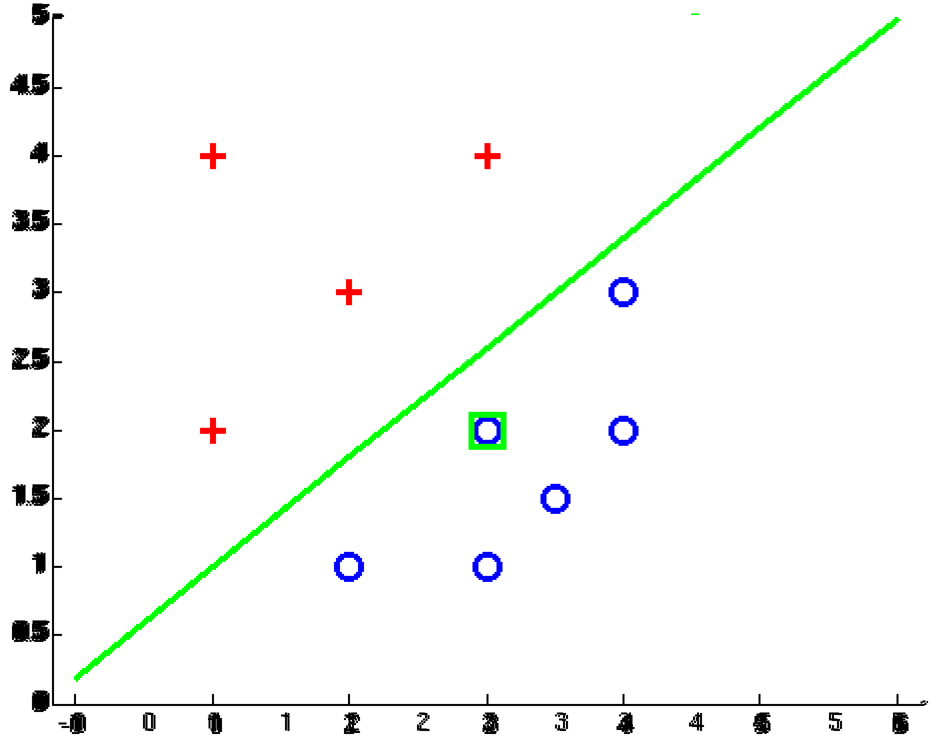
  - If correct (i.e., y=y*), no change!
  - If wrong: adjust the weight vector by adding or subtracting the feature vector. Subtract if y* is -1.

$$w = w + y^* \cdot f$$



# Examples: Perceptron

- Separable Case



# Multiclass Decision Rule

- If we have multiple classes:
  - A weight vector for each class:

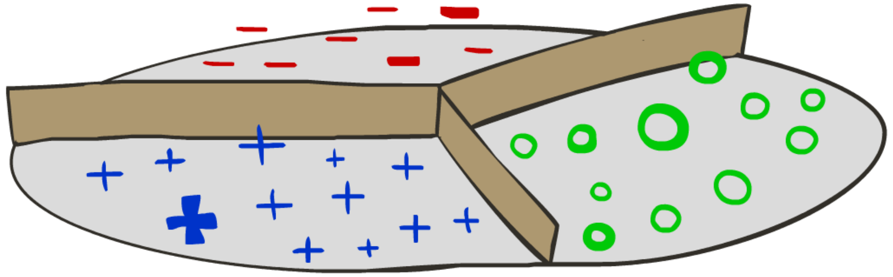
    $$w_y$$

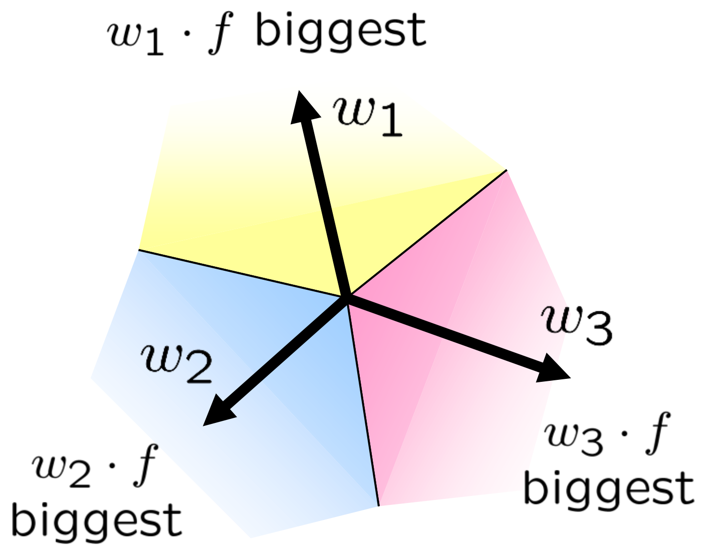
  - Score (activation) of a class y:

    $$w_y \cdot f(x)$$

  - Prediction highest score wins

    $$y = \arg\max_y \; w_y \cdot f(x)$$





*Binary = multiclass where the negative class has weight zero*

# Learning: Multiclass Perceptron

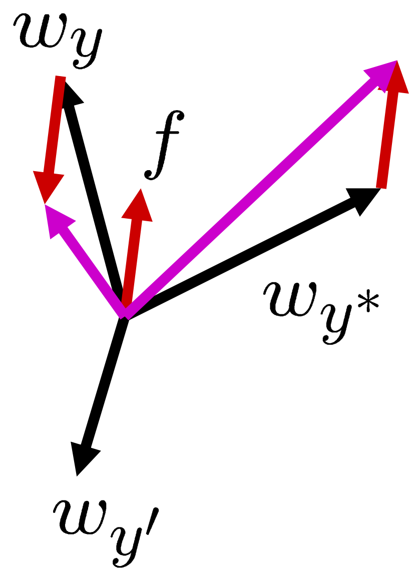
- Start with all weights = 0
- Pick up training examples one by one
- Predict with current weights

$$y \;= \arg\max_y \; w_y \cdot f(x)$$

- If correct, no change!
- If wrong: lower score of wrong answer, raise score of right answer

$$w_y = w_y - f(x)$$

$$w_{y^*} = w_{y^*} + f(x)$$



# Example: Multiclass Perceptron

"win the vote" [1 1 0 1 1]

"win the election" [1 1 0 0 1]

"win the game" [1 1 1 0 1]

$w_{SPORTS}$

1 -2 -2

```
BIAS  : 1
win   : 0
game  : 0
vote  : 0
the   : 0
...
```

| | |
|---|---|
| 0 | 1 |
| -1 | 0 |
| 0 | 1 |
| -1 | -1 |
| -1 | 0 |

$w_{POLITICS}$

0 3 3

```
BIAS  : 0
win   : 0
game  : 0
vote  : 0
the   : 0
...
```

| | |
|---|---|
| 1 | 0 |
| 1 | 0 |
| 0 | -1 |
| 1 | 1 |
| 1 | 0 |

$w_{TECH}$

0 0

```
BIAS  : 0
win   : 0
game  : 0
vote  : 0
the   : 0
...
```

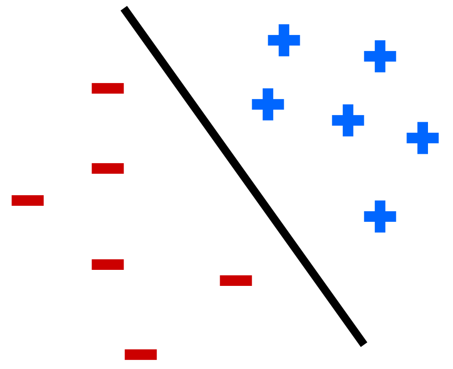
# Properties of Perceptrons

- Separability: true if some parameters get the training set perfectly correct

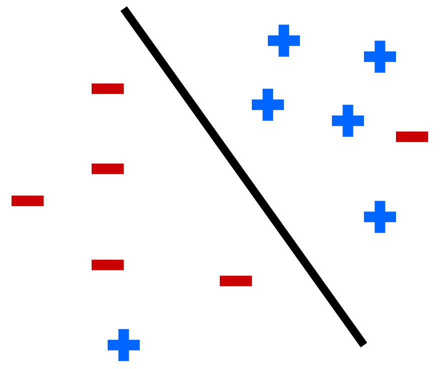
- Convergence: if the training is separable, perceptron will eventually converge (binary case)

- Non-separable?

Separable

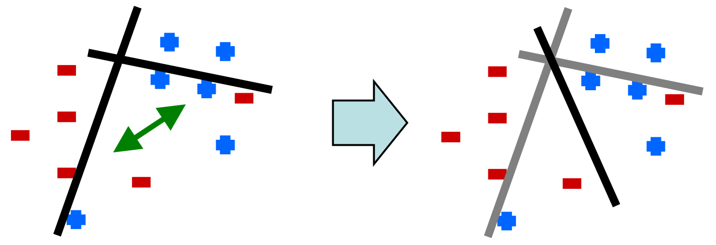


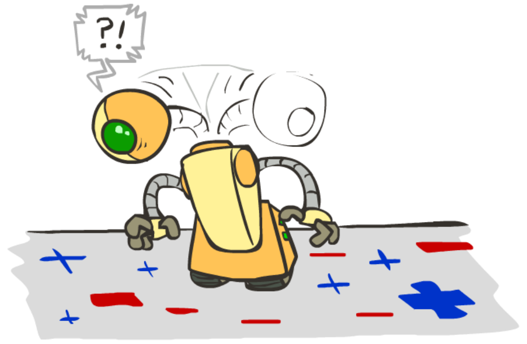
Non-Separable



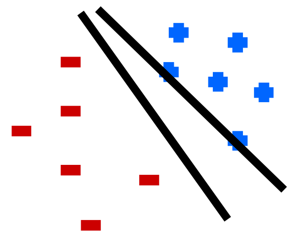
# Problems with the Perceptron

- Noise: if the data isn't separable, weights might thrash
  - Averaging weight vectors over time can help (averaged perceptron)

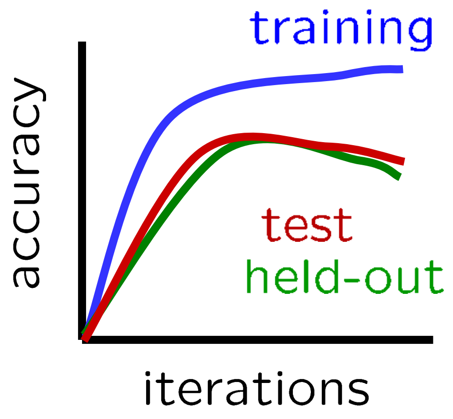


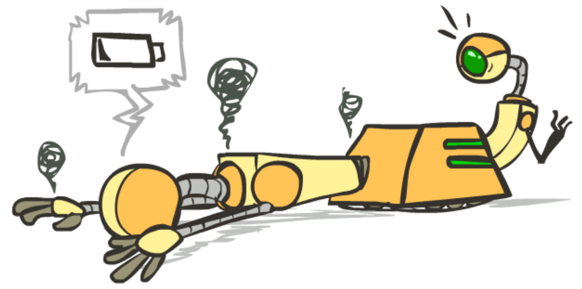


- Mediocre generalization: finds a "barely" separating solution

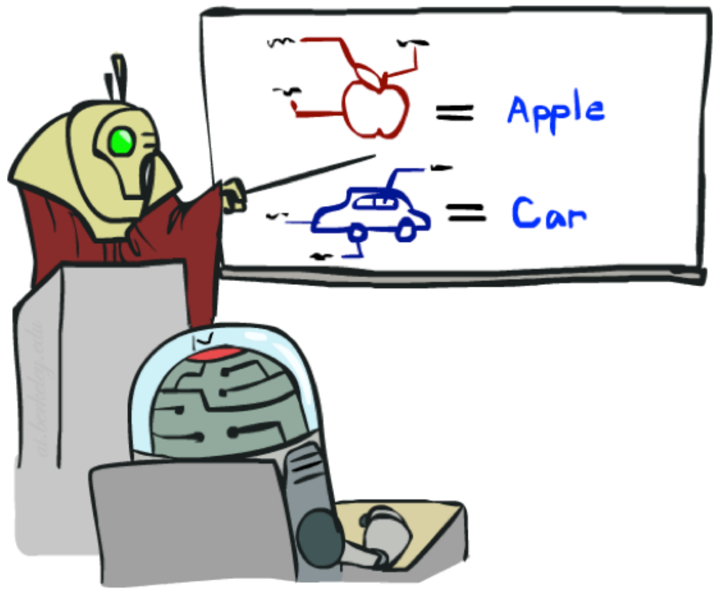


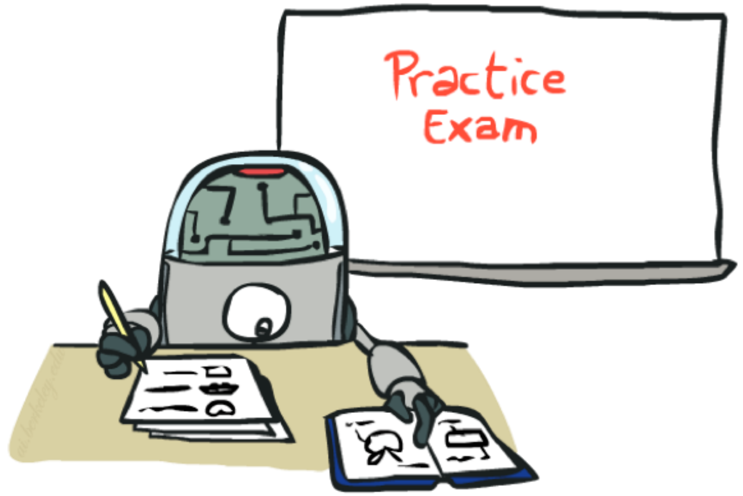
- Overtraining: test / held-out accuracy usually rises, then falls
  - Overtraining is a kind of overfitting

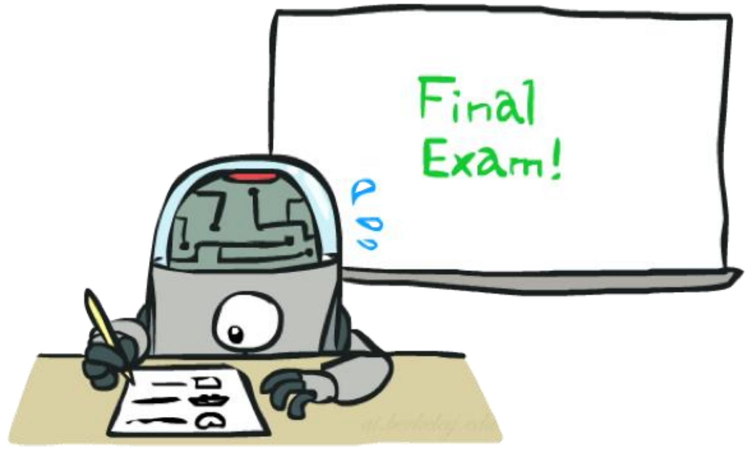




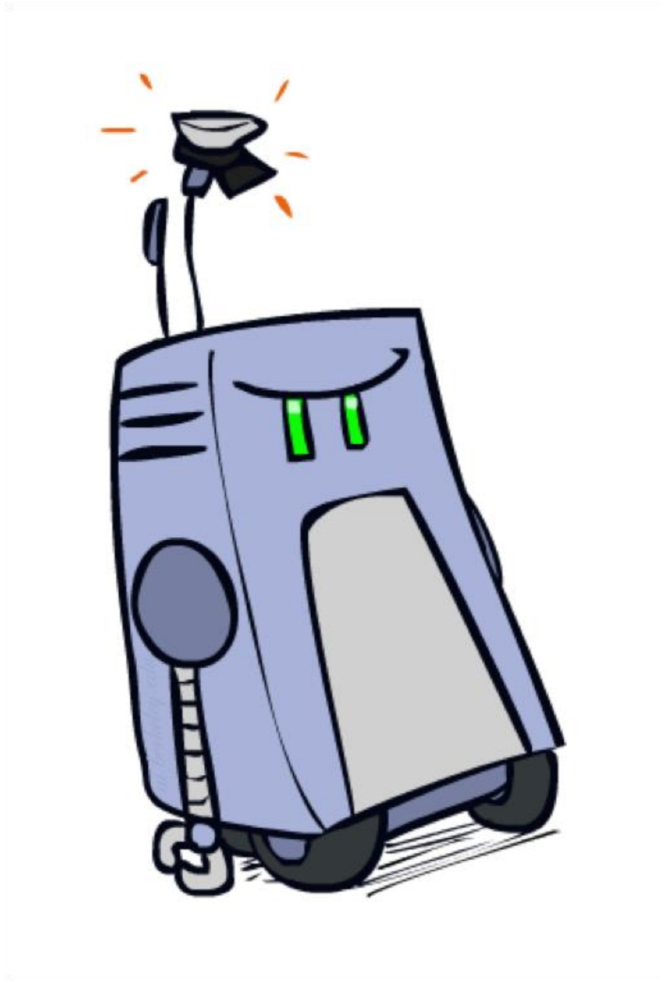
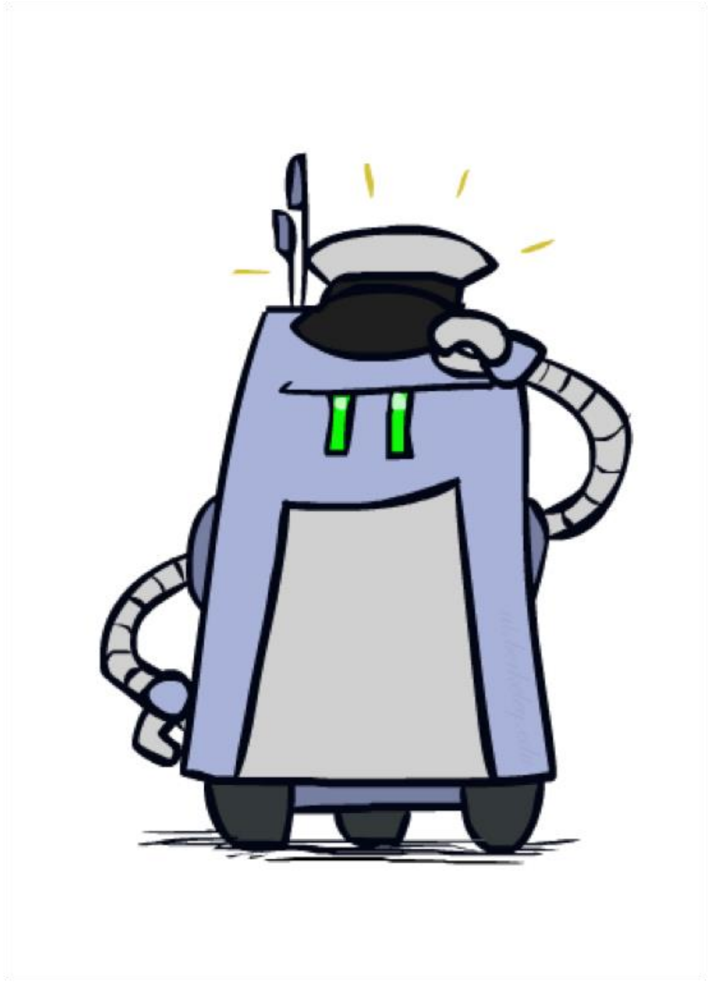
## Training and Testing







# Underfitting and Overfitting

# Overfitting

- Too many features
  - Spam if contains “FREE!”
  - Spam if contains $dd, CAPS
  - …
  - Spam if contains “Sir”
  - Spam if contains address
  - Spam if contains “OT”
  - …

✗

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# Example: Overfitting

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

$P(C = 2) = 0.1$

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

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

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

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

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

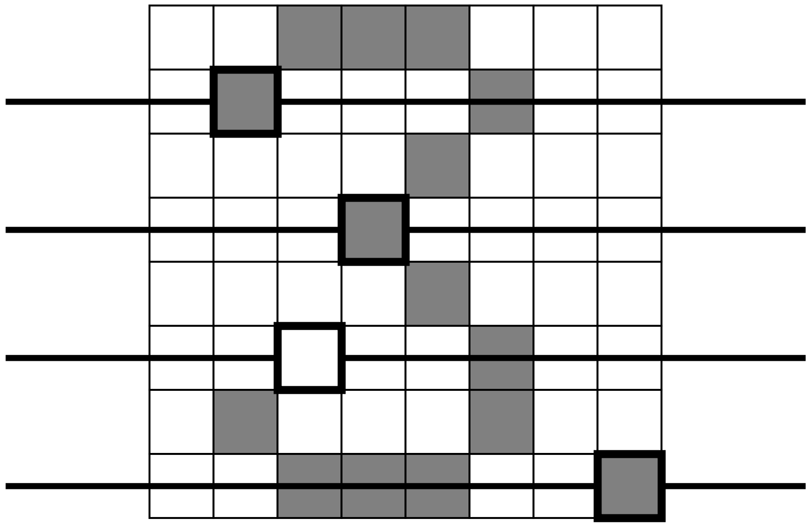
$P(C = 3) = 0.1$

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

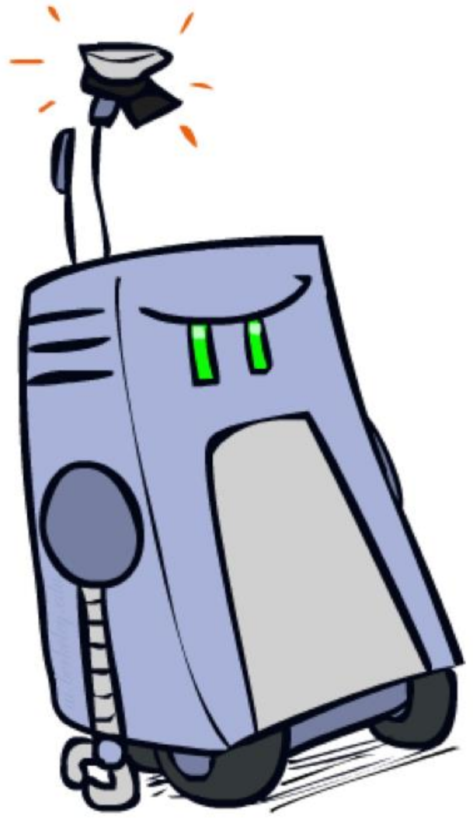
$P(\text{on}|C = 3) = 0.9$

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

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



*2 wins!!*



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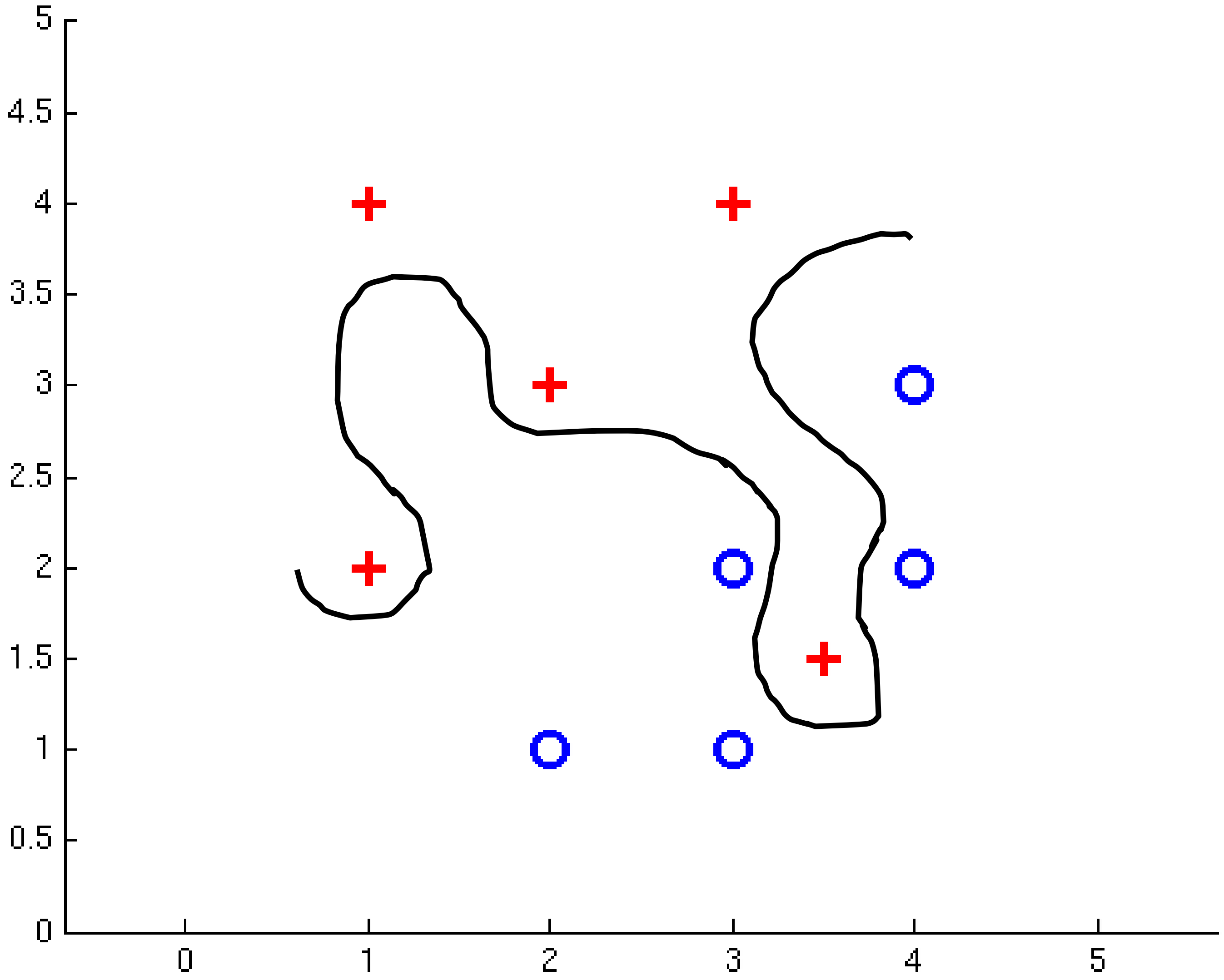
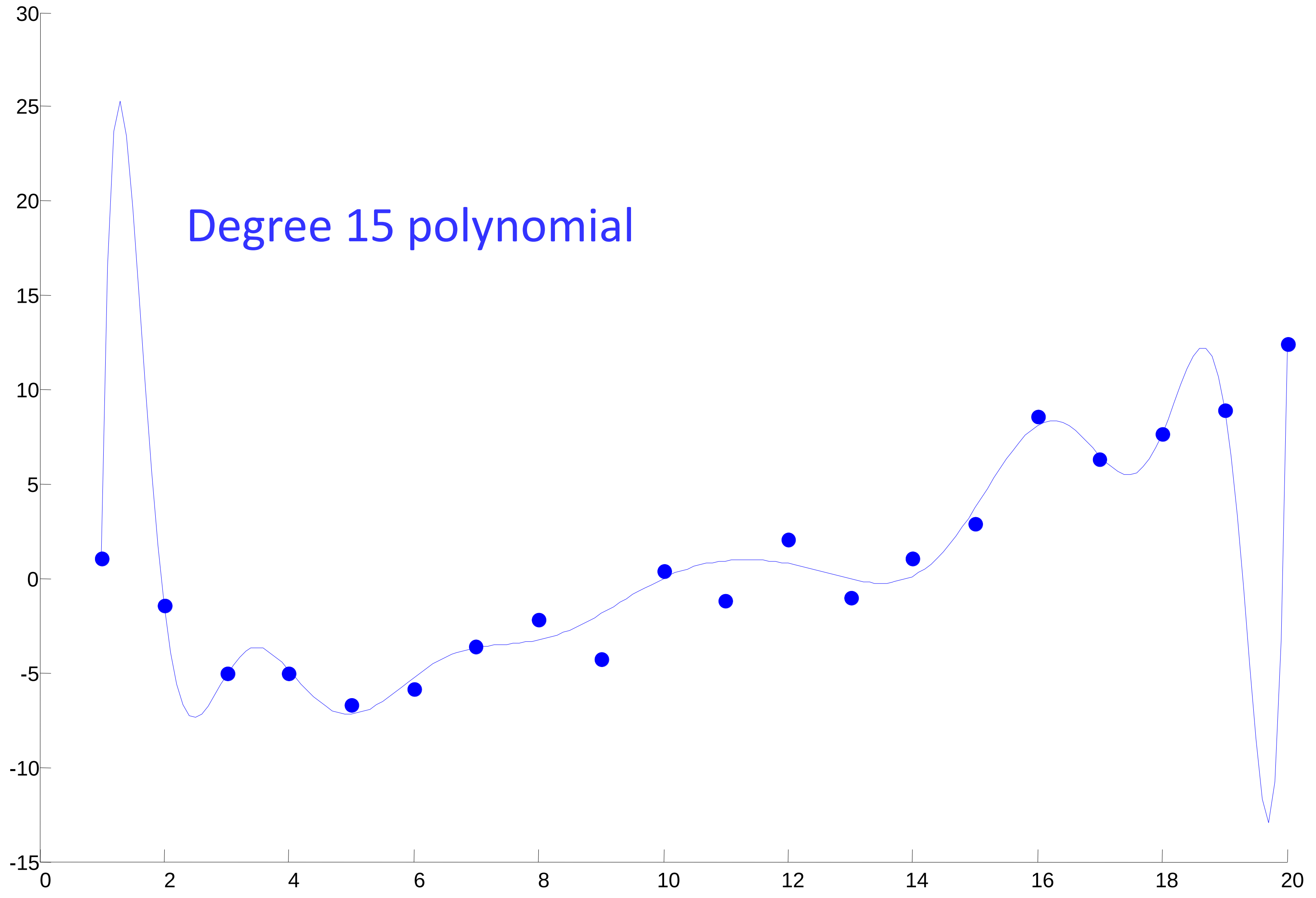
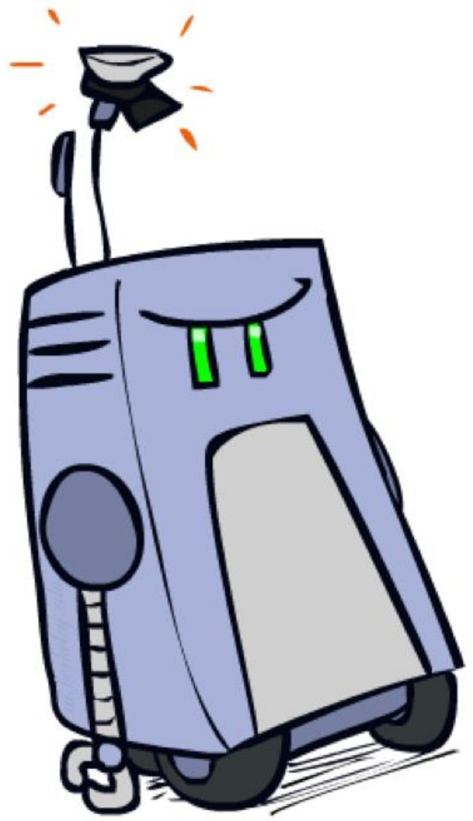
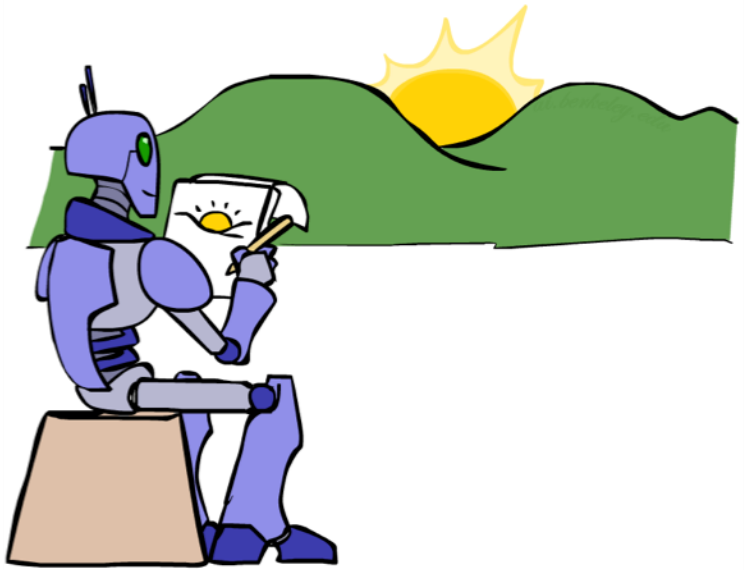


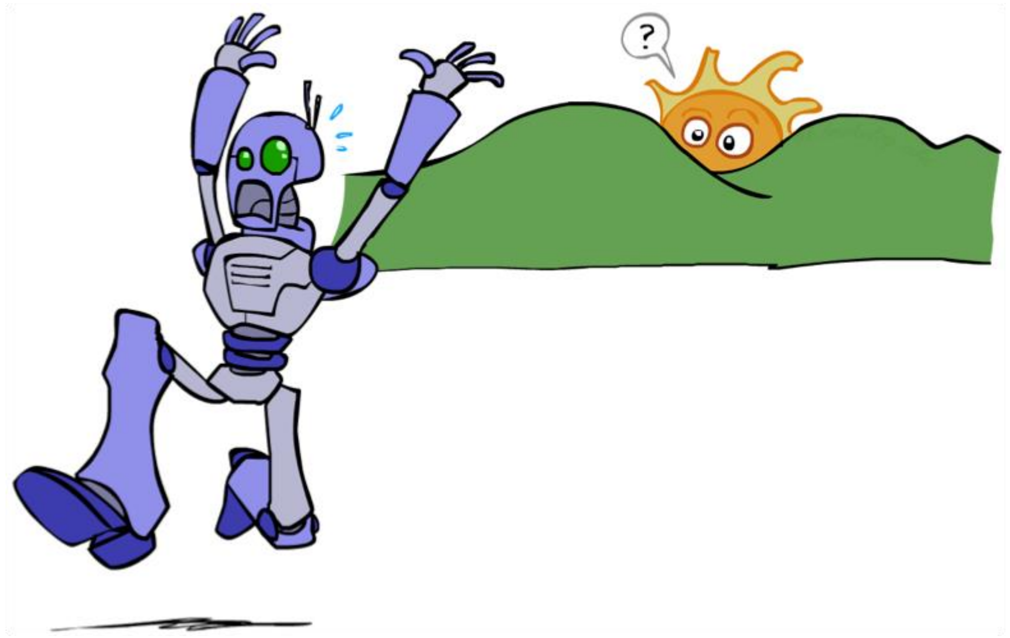
# Overfitting





## Unseen Events





# Generalization and Overfitting

- Relative frequency parameters will overfit the training data!
  - Just because we never saw a non-spam email with an address 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

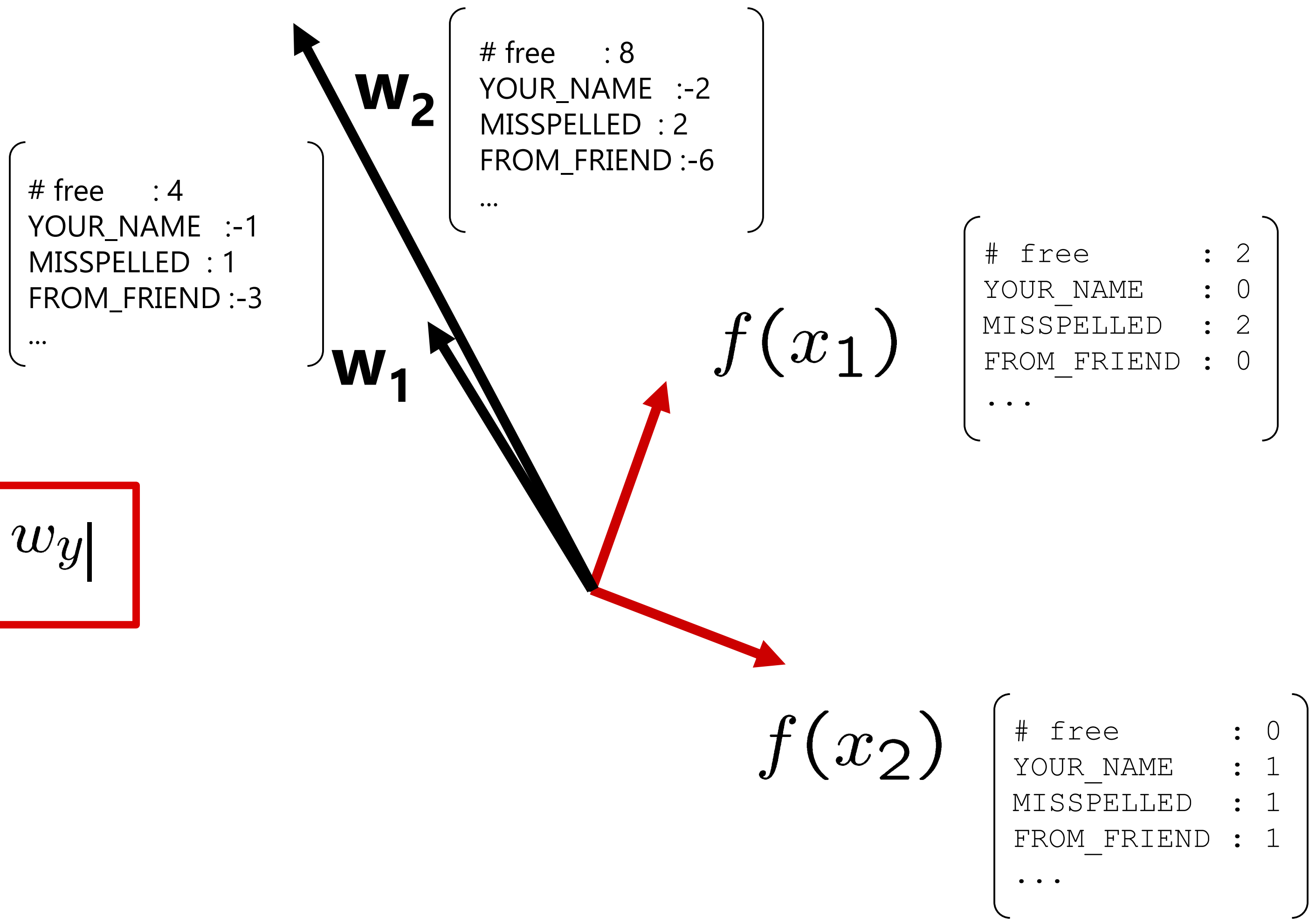
- As an extreme case, imagine using the entire email as the only feature
  - Would get the training data perfect (if deterministic labeling)
  - Wouldn't *generalize* at all
  - Just making the bag-of-words assumption gives us some generalization, but isn't enough

- To generalize better: we need to smooth or regularize the estimates

# Regularization

- Limit the number of features
- Limit the norm of the vector **w**
  - If **w₁** and **w₂** are equally good, and |**w₁**|>|**w₂**|, then **w₂** is likely to better generalize

$$y = \arg\max_y \boxed{w_y \cdot f(x) - |\, w_y|}$$



| | |
|---|---|
| # free | : 4 |
| YOUR_NAME | :-1 |
| MISSPELLED | : 1 |
| FROM_FRIEND | :-3 |
| … | |

| | |
|---|---|
| # free | : 8 |
| YOUR_NAME | :-2 |
| MISSPELLED | : 2 |
| FROM_FRIEND | :-6 |
| … | |

```
# free       : 2
YOUR_NAME    : 0
MISSPELLED   : 2
FROM_FRIEND  : 0
...
```

```
# free       : 0
YOUR_NAME    : 1
MISSPELLED   : 1
FROM_FRIEND  : 1
...
```

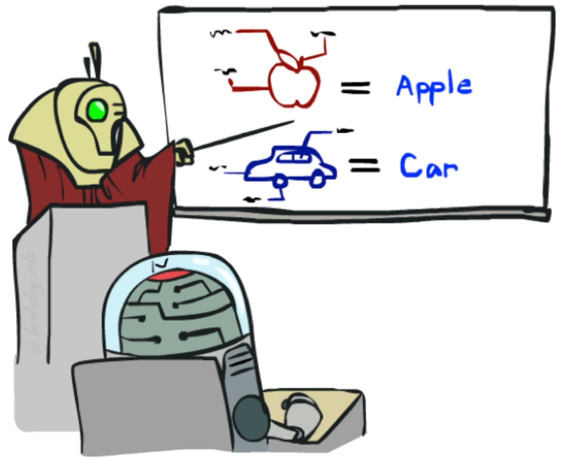
# Important Concepts

- Data: labeled instances, e.g. emails marked spam/ham
  - Training set
  - Held out 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 held-out set)
  - Compute accuracy on 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
  - <u>Overfitting</u>: fitting the training data very closely, but not generalizing well
  - <u>Underfitting</u>: fits the training set poorly

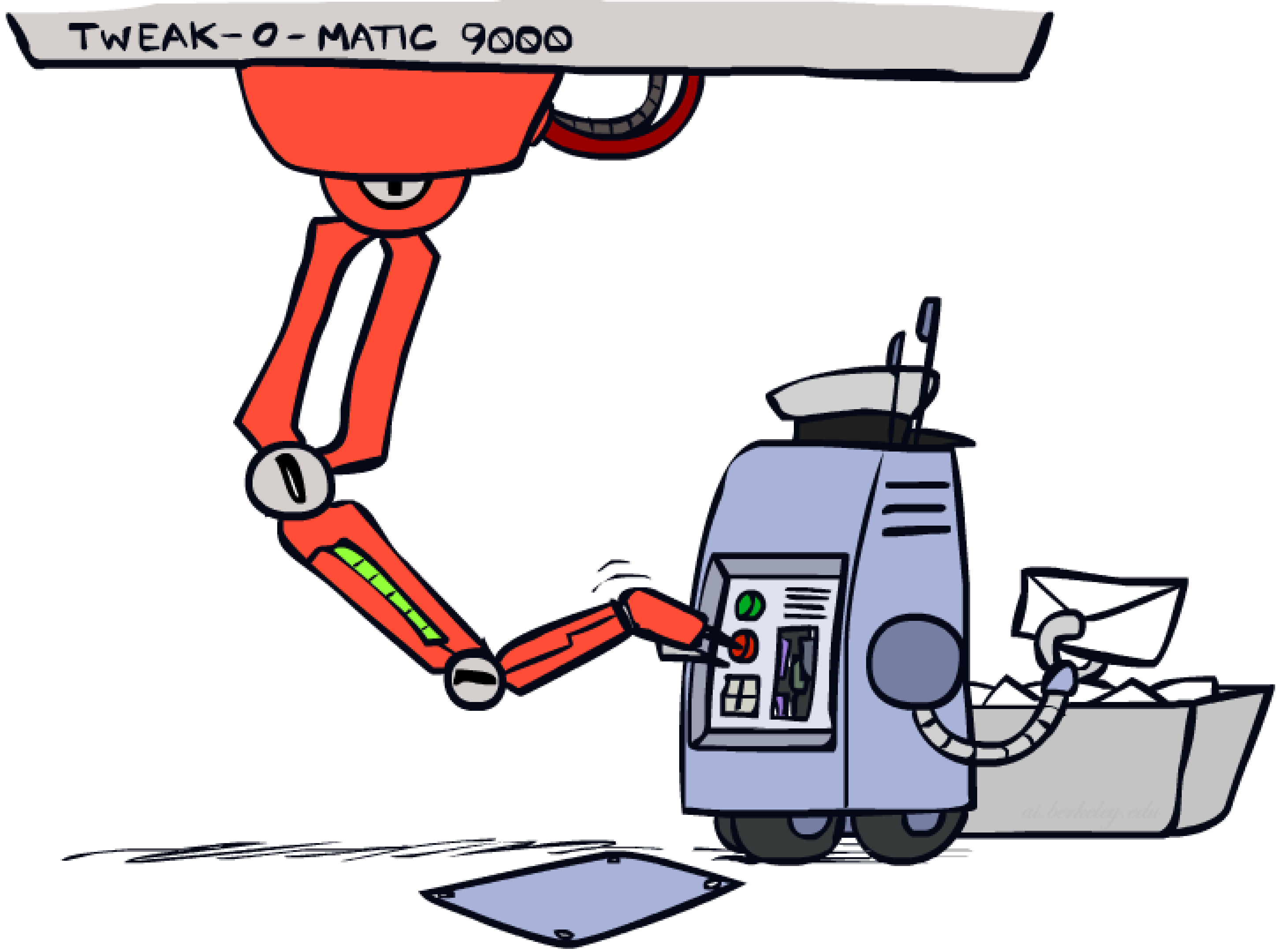
Training Data

Held-Out Data

Test Data



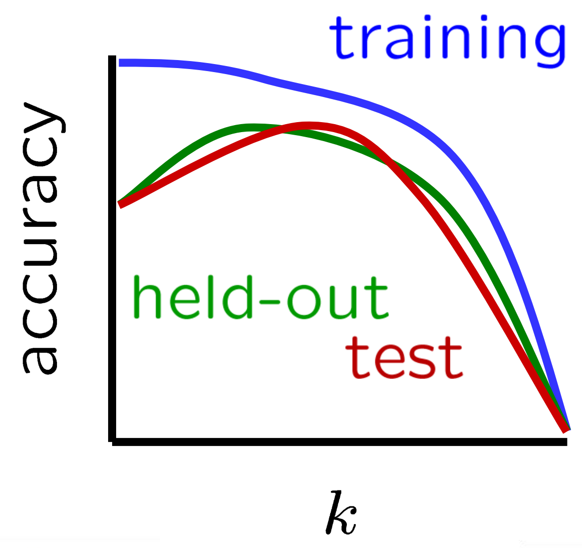
## Tuning

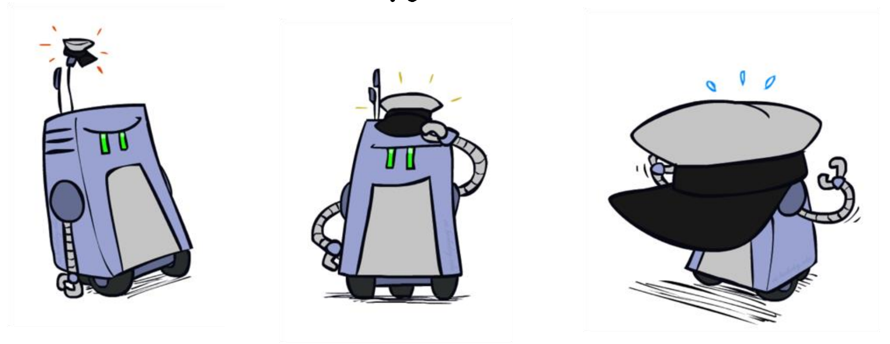


# Tuning on Held-Out Data

- Now we've got two kinds of unknowns
  - Parameters: the probabilities P(X|Y), P(Y)
  - Hyperparameters: e.g. the amount / type of smoothing to do, k, $\alpha$

- 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 held-out data
  - Choose the best value and do a final test on the test data





# Practical Tip: 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

## Improving the Perceptron: Next lecture!