# 11. MACHINE LEARNING – SYSTEM DESIGN

# Machine learning System design

## Prioritizing what to work on:

### Building a spam classifier:

- Supervised learning
- x = features of mail
  y = spam (1), no spam (0)

Features: choose 100 word indicative of spam/not spam
e.g. deal, discount, buy, andrew, now ...

$$x = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ \vdots \\ 1 \end{bmatrix} \begin{matrix} \text{andrew} \\ \text{buy} \\ \text{deal} \\ \text{discount} \\ \vdots \\ \text{now} \end{matrix}$$

Verify if this words occure in mail

$x \in \mathbb{R}^{100}$

Note:
In practice, take most frequently occuring n words (10'000-50'000) in training set, rather then picking 100 words manually.

$$x_j = \begin{cases} 0 & \text{- if word does not} \\ 1 & \text{appear in email, 1 otherwise} \end{cases}$$

How to spend your time to make it have low error?
- Collect lots of data (e.g. Honeypot project)
- Develop sophisticated features based on email routing information (from email header)
- Develop sophisticated features for messages body, should "discount" and "discounts" be treated as the same word? How about "deal" and "Dealer"? Features about punctuation?
- Develop sophisticated features to detect misspellings (e.g. m0rtgages, med1cine, w4tches.)

## Recommended approach:

- Start with an algorithm that you can implement quickly. Implement it and test it on your cross validation data.
- Plot learning curves to decide if more data, more features etc. are likely to help.
- Error analysis: Manually examine the examples (in cross-validation set) that your algorithm made errors on. See if you spot any systematic trend in what type of examples it is making errors on.

→ let evidence guide your decissions.

try to spot systematic errors !

## Error analysis

$m_{cv}$ = 500 examples in cross validation set
Algorithm misclassifies 100 emails
Manually examine the 100 errors, and categorize them based on:
1) what type of email it is → eg. pharma, replica, steal pw ...
2) what cues (features) you think would have helped the algorithm classify them correctly.

| | | | |
|---|---|---|---|
| Pharma: | 12 | Deliberately misspelling: | 5 |
| Replica/Fake: | 4 | Unusual email routing: | 16 |
| Steal pw: | 53 → target this problem | Unusual punctuation: | 32 |
| Others: | 31 | | |

## The importance of numerical evaluation:

- Should discout / discounted / discounting to be treated as the same word?
  ↳ Can use "stemmer" software → eg. "Porter Stemmer", but this can also be misleading universe / university
- Error analysis might not be helpful for deciding if this is likely to improve performance. Only solution is to try and see if it works.
- Need numerical evaluation (e.g. cross_val. error) of algorithms with and without stemming. without stemming: 5% err with stemming: 3% err.
  Distinguish upper vs. lower case (Hon / mon) → 3% → 2%..

Use cross validation error for numerical evaluation

## Cancer classification example

Train logistic regression ~~problem~~ model $h_\theta(x)$. $y=1$ if cancer, $y=0$ if no
Find that you get 1% error on the test set. (99% correct diagnoses)
=> only 0,5% of patients have cancer.

↳ skewed classes => a lot more $y=0$ classes as $y=1$

function $y$ = predictCancer($x$)
  $y=0$; % ignore $x$!
return

=> Error 0,5%
→ not a good approach

## Precision / Recall

$y=1$ in presence of rare classes that we want to detect.

| | | Actual class 1 | Actual class 0 |
|---|---|---|---|
| Predicted class | 1 | True positive | False positive |
| | 0 | False negative | True negative |

$y=0$
Recall $=0$

### Precision

Of all patients where we predicted $y=1$, what fraction actually has cancer?

$$\frac{\text{True pos.}}{\#\text{predict. pos}} = \frac{\text{True positives}}{\text{True pos. + false pos.}}$$

↳ high precision would be good

### Recall

Of all patients that actually have cancer, what fraction did we correctly detect as having cancer?

$$\frac{\text{True pos.}}{\#\text{actual pos.}} = \frac{\text{True positives}}{\text{True pos + false neg.}}$$

$y=1$ by presence of rare class?

Logistic regression: $0 \leq h_\theta(x) \leq 1$

Predict 1 if $h_\theta(x) \geq 0.5$ => 0.7 => 0.9

Predict 0 if $h_\theta(x) < 0.5$ => 0.7 => 0.9

Suppose we want to predict $y=1$ (cancer) only if very confident.

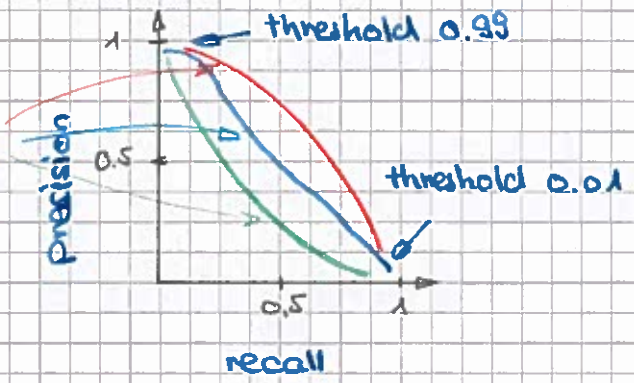
↳ setting thresholdes to 0.7 or 0.9 => higher precision, lower recall

Suppose we want to avoid missing too many cases of cancer (avoid false negative)

↳ setting thresholdes to 0.3 (more conservative) => higher recall, lower precision

More generally: Predict 1 if $h_\theta(x) \geq$ threshold

Precision/recall curve can have different shapes




## $F_1$ Score (F score)

How to compare precision/recall numbers?

| | Precision (P) | Recall (R) | Average | $F_1$ Score |
|---|---|---|---|---|
| Algorithm 1 | 0.5 | 0.4 | 0.45 | 0.444 ← |
| Algorithm 2 | 0.7 | 0.1 | 0.4 | 0.175 |
| Algorithm 3 | 0.02 | 1.0 | 0.51 | 0.0392 => predict $y=1$ all the time => not very good! |

$$\text{Average} = \frac{P+R}{2}$$

$$F_1 \text{ Score} = 2 \cdot \frac{PR}{P+R}$$

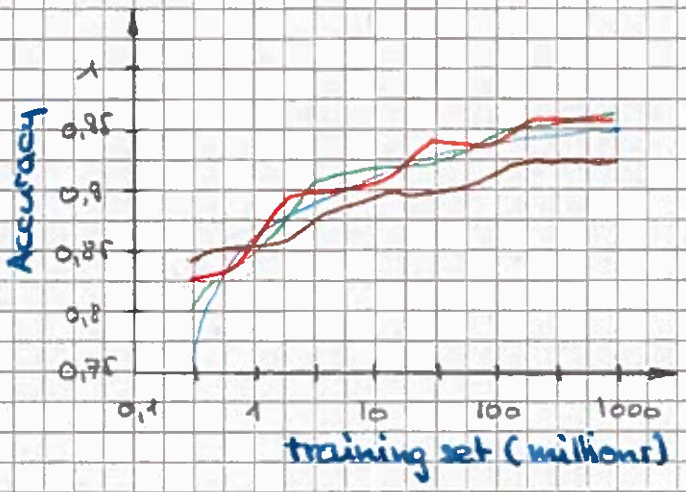
$P = 0$ or $R = 0$ => F Score $= 0$

$P = 1$ and $R = 1$ => F Score $= 1$

Designing a high accuracy learning system

e.g Classify between confusable words {to, two, too}, {then, than}
=> For breakfast I ate ____ eggs.

Algorithms:
- Perceptron —
- Winnow —
- Memory based —
- Naive Bayes —




"It's not who has the best algorithm that wins. It's who has the most data"

## Large data rationale

Assume feature $x \in \mathbb{R}^{n+1}$ has sufficient information to predict y accurately.

Example: For breakfast I ate ____ eggs. (to / two / too)

Counter example: Predict housing prices from only size (feet²) and no other features.

Useful test: Given the input x, can a human expert confidently predict y?

## Large data rationale

Use a learning algorithm with many parameters (e.g. logistic_regression / linear regression with many features; neural network with many hidden units).

=> low bias algorithm

=> $J_{train}(\theta)$ will be small.

Use a very large training set (unlikely to overfit) low variance

$J_{train}(\theta) \approx J_{test}(\theta)$

$J_{test}(\theta)$ will be small