

# CPSC 340: Machine Learning and Data Mining

Probabilistic Classification

Fall 2021

# Admin

- Assignment 1 is due tonight: you should be almost done.
  - You can use 1 late day to submit Saturday, 2 for Sunday.
  - Solutions will go up on Monday.
- Waiting list people: everyone should be in.
- Auditors:
  - Bring your forms at the end of class, or email them today.

# Last Time: Training, Testing, and Validation

- **Training step:**

Input: set of 'n' training examples  $x_i$  with labels  $y_i$

Output: a model that maps from arbitrary  $x_i$  to a  $\hat{y}_i$

- **Prediction step:**

Input: set of 'l' testing examples  $\tilde{x}_i$  and a model.

Output: predictions  $\hat{y}_i$  for the testing examples.

- What we are interested in is the **test error**:

- Error made by prediction step on new data.

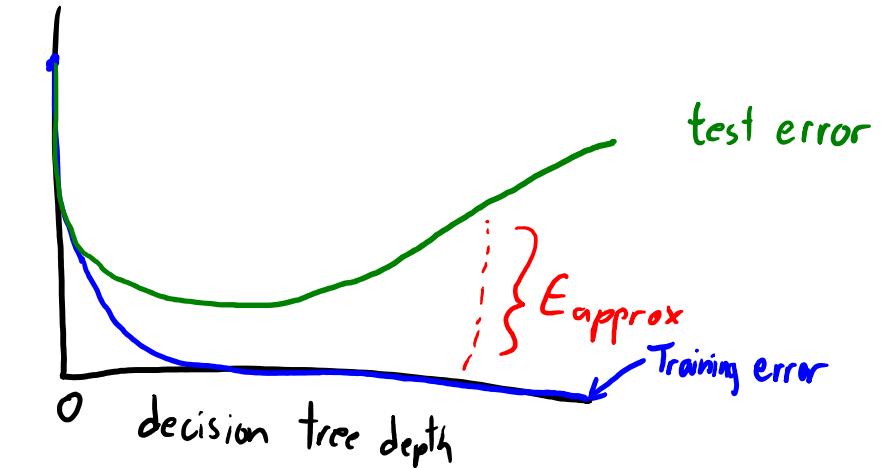
# Last Time: Fundamental Trade-Off

- We decomposed test error to get a fundamental trade-off:

$$E_{\text{test}} = E_{\text{approx}} + E_{\text{train}}$$

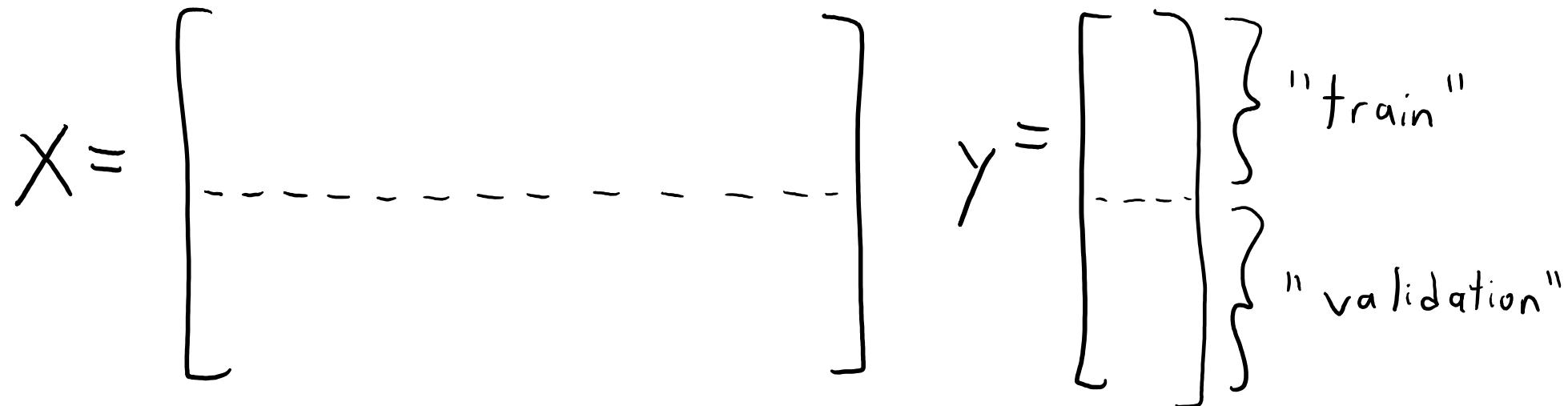
*"test error"*      *"approximation error"*      *"training error"*

- Where  $E_{\text{approx}} = (E_{\text{test}} - E_{\text{train}})$ .
- $E_{\text{train}}$  goes down as model gets complicated:
  - Training error goes down as a decision tree gets deeper.
- But  $E_{\text{approx}}$  goes up as model gets complicated:
  - Training error becomes a worse approximation of test error.



# Last Time: Validation Error

- **Golden rule:** we can't look at test data during training.
- But we can approximate  $E_{\text{test}}$  with a **validation error**:
  - Error on a set of training examples we “hid” during training.



- Find the **decision tree** based on the “train” rows.
- Validation error is the **error of the decision tree** on the “validation” rows.
  - We typically choose “hyper-parameters” like depth to minimize the validation error.

# Overfitting to the Validation Set?

- Validation error usually has lower optimization bias than training error.
  - Might optimize over 20 values of “depth”, instead of millions+ of possible trees.
- But we can still overfit to the validation error (common in practice):
  - Validation error is only an unbiased approximation if you use it once.
  - Once you start optimizing it, you start to overfit to the validation set.
- This is most important when the validation set is “small”:
  - The optimization bias decreases as the number of validation examples increases.
- Remember, our goal is still to do well on the test set (new data), not the validation set (where we already know the labels).

# Should you trust them?

- Scenario 1:
  - “I built a model based on the data you gave me.”
  - “It classified your data with 98% accuracy.”
  - “It should get 98% accuracy on the rest of your data.”
- Probably not:
  - They are reporting training error.
  - This might have nothing to do with test error.
  - E.g., they could have fit a very deep decision tree.
- Why ‘probably’?
  - If they only tried a few very simple models, the 98% might be reliable.
  - E.g., they only considered decision stumps with simple 1-variable rules.

# Should you trust them?

- Scenario 2:
  - “I built a model based on half of the data you gave me.”
  - “It classified the other half of the data with 98% accuracy.”
  - “It should get 98% accuracy on the rest of your data.”
- Probably:
  - They computed the validation error once.
  - This is an unbiased approximation of the test error.
  - Trust them if you believe they didn’t violate the golden rule.

# Should you trust them?

- Scenario 3:
  - “I built 10 models based on half of the data you gave me.”
  - “One of them classified the other half of the data with 98% accuracy.”
  - “It should get 98% accuracy on the rest of your data.”
- Probably:
  - They computed the validation error a small number of times.
  - Maximizing over these errors is a biased approximation of test error.
  - But they only maximized it over 10 models, so bias is probably small.
  - They probably know about the golden rule.

# Should you trust them?

- Scenario 4:
  - “I built **1 billion models** based on half of the data you gave me.”
  - “**One of them** classified the **other half of the data** with 98% accuracy.”
  - “It should get 98% accuracy on the rest of your data.”
- **Probably not:**
  - They computed the validation error **a huge number of times**.
  - They tried so many models, one of them is likely to work by chance.
- Why ‘probably’?
  - If the 1 billion models were all *extremely* simple, 98% might be reliable.

# Should you trust them?

- Scenario 5:
  - “I built 1 billion models based on the first third of the data you gave me.”
  - “One of them classified the second third of the data with 98% accuracy.”
  - “It also classified the last third of the data with 98% accuracy.”
  - “It should get 98% accuracy on the rest of your data.”
- Probably:
  - They computed the first validation error a huge number of times.
  - But they had a second validation set that they only looked at once.
  - The second validation set gives unbiased test error approximation.
  - This is ideal, as long as they didn’t violate golden rule on the last third.
  - And assuming you are using IID data in the first place.

# Train/Validation/Test Terminology

- **Training** set: used (a lot) to set parameters.
- **Validation** set: used (a few times) to set hyper-parameters.
- **Testing** set: used (once) to evaluate final performance.
- **Deployment** (real-world): what you really care about.

|            | fit | score | predict |
|------------|-----|-------|---------|
| Train      | ✓   | ✓     | ✓       |
| Validation |     | ✓     | ✓       |
| Test       |     | once  | once    |
| Deployment |     |       | ✓       |

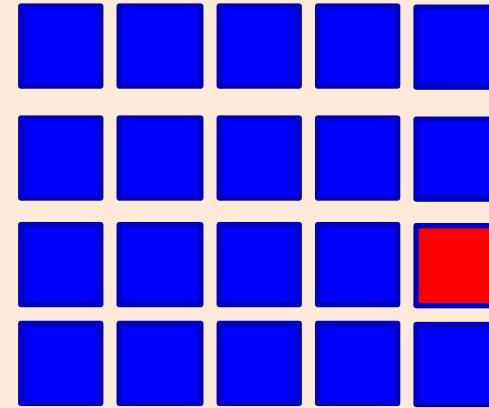
# Validation Error and Optimization Bias

- Optimization bias is small if you only compare a few models:
  - Best decision tree on the training set among depths 1, 2, 3,..., 10.
  - Risk of overfitting to validation set is low if we try 10 things.
- Optimization bias is large if you compare a lot of models:
  - All possible decision trees of depth 10 or less.
  - Here we're using the validation set to pick between a billion+ models:
    - Risk of overfitting to validation set is high: could have low validation error by chance.
  - If you did this, you might want a second validation set to detect overfitting.
- And optimization bias shrinks as you grow size of validation set.

*bonus!*

## Aside: Optimization Bias leads to Publication Bias

- Suppose that 20 researchers perform the exact same experiment:



- They each test whether their effect is “significant” ( $p < 0.05$ ).
  - 19/20 find that it is not significant.
  - But the 1 group finding it’s significant publishes a paper about the effect.
- This is again optimization bias, contributing to publication bias.
  - A contributing factor to many reported effects being wrong.

# Cross-Validation (CV)

- Isn't it wasteful to only use part of your data?
- 5-fold cross-validation:
  - Train on 80% of the data, validate on the other 20%.
  - Repeat this 5 more times with different splits, and average the score.

$$X = \begin{bmatrix} \dots & \dots & \dots \\ \dots & \dots & \dots \end{bmatrix} \quad y = \begin{bmatrix} \dots \\ \dots \\ \dots \\ \dots \\ \dots \end{bmatrix} \quad \left\{ \begin{array}{l} \text{"fold" 1} \\ \text{"fold" 2} \\ \text{"fold" 3} \\ \text{"fold" 4} \\ \text{"fold" 5} \end{array} \right.$$

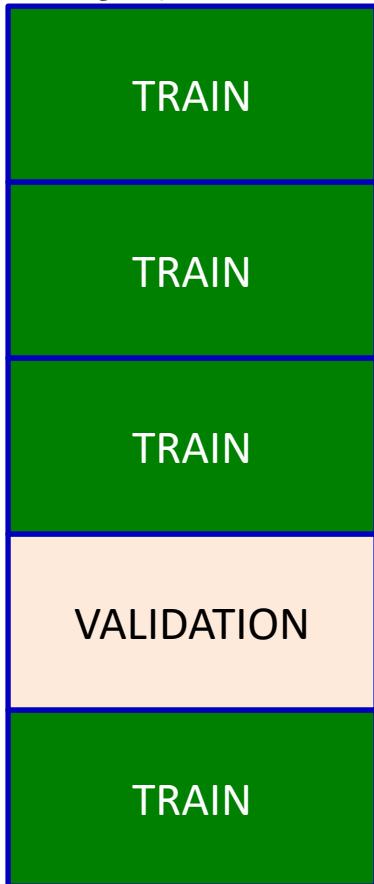
1. Train on folds  $\{1, 2, 3, 4\}$ , compute error on fold 5.
2. Train on folds  $\{1, 2, 3, 5\}$ , compute error on fold 4.
3. Train on folds  $\{1, 2, 4, 5\}$ , compute error on fold 3.
- ⋮
6. Take average of the 5 errors as approximation of test error

# Cross-Validation (CV)

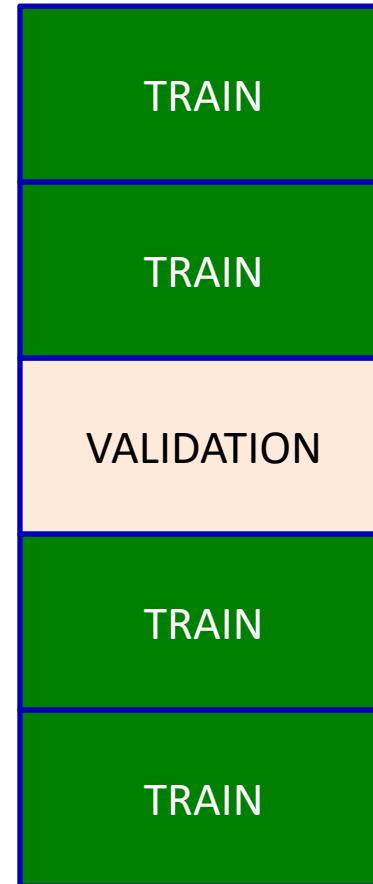
Fold 1:



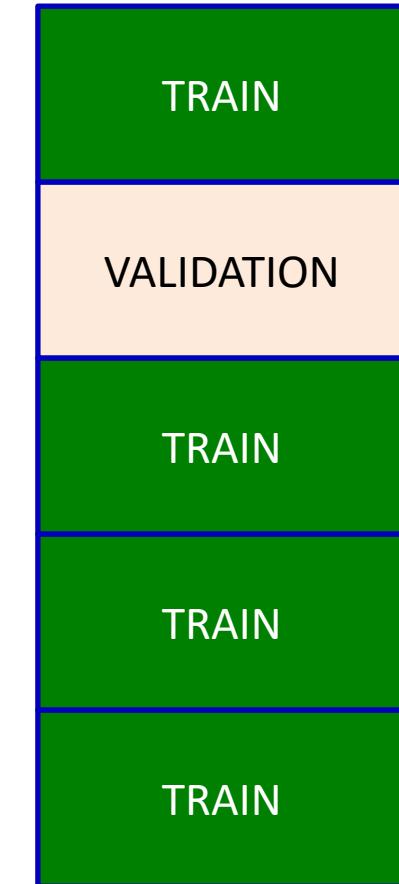
Fold 2:



Fold 3:



Fold 4:



Fold 5:



Error: 0.1

Error: 0.2

Error: 0.2

Error: 0.1

Error: 0.2

CV error estimate for this hyper-parameter:  $\text{mean}(\text{errors}) = 0.16$

# Cross-Validation Pseudo-Code

To choose depth

for depth in 1:20

    compute cross-validation score

return depth with highest score

To compute 5-fold cross-validation score:

for fold in 1:5

    train 80% that doesn't include fold

    test on fold

return average test error

Notes:

- This fits 100 models!  
(20 depths times 5 folds)
- We get one (average) score for each of the 20 depths.
- Use this score to pick depth

# Cross-Validation (CV)

- You can take this idea further (“k-fold cross-validation”):
  - **10-fold cross-validation**: train on 90% of data and validate on 10%.
    - Repeat 10 times and average (test on fold 1, then fold 2,..., then fold 10),
  - **Leave-one-out cross-validation**: train on all but one training example.
    - Repeat n times and average.
- Mean score gets **more accurate** but **more expensive** with more folds.
  - To choose depth we compute the **cross-validation score** for each depth.
- As before, if data is ordered then folds should be random splits.
  - Randomize first, then split into **fixed folds**.

(pause)

# The “Best” Machine Learning Model

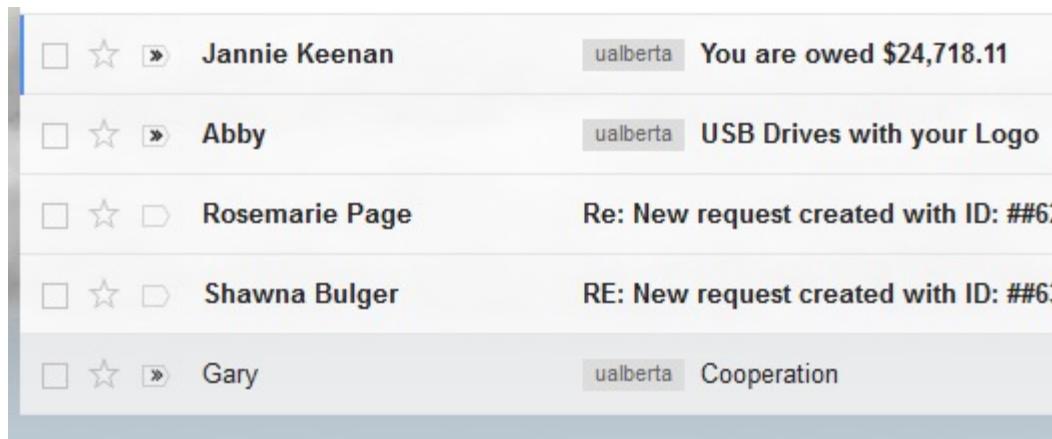
- Decision trees are not always most accurate on test error.
- What is the “best” machine learning model?
- Usual measure of performance is the generalization error:
  - Average error for a random new  $(x, y)$  from the (hypothetical) data distribution.
  - “How well we expect to do on a *completely fresh* test set.”
- No free lunch theorem (proof in bonus slides):
  - There is no “best” model achieving the best generalization error for every problem.
  - If model A generalizes better to new data than model B on one dataset, there is another dataset where model B works better.
- This question is like asking which is “best” among “rock”, “paper”, and “scissors.”

# The “Best” Machine Learning Model

- Implications of the lack of a “best” model:
  - We need to learn about and **try out multiple models**.
- So which ones to study in CPSC 340?
  - We’ll usually motivate each method by a specific application.
  - But we’re focusing on **models that have been effective in many applications**.
- Caveat of no free lunch (NFL) theorem:
  - The world is very structured.
    - But proof of the no-free-lunch theorem **assumes any map from  $x_i$  to  $y_i$  is equally likely**.
    - **Some datasets are more likely than others**.
    - Model A really could be better than model B on every real dataset in practice.
- Machine learning research:
  - Large focus on models that are **useful across many applications**.

# Application: E-mail Spam Filtering

- Want to build a system that **detects spam e-mails**.
  - Context: spam used to be a big problem.



**Gary <jaiwasie@mail.com>**  
to schmidt ▾

**⚠ Be careful with this message.** Similar messages were used to steal people's personal information. [Learn more](#)

Hey,

Do you have a minute today?  
Are you interested to use our email marketing and lead generation solutions?  
We have worked on a number of projects and campaigns in many industries since 2007

Please reply today so we can go over options for you.  
I am sure we can help to grow your business soon by using our mailing services.

Best regards,  
Gary  
Contact: abelfong@sina.com

- Can we formulate as **supervised learning**?

# Spam Filtering as Supervised Learning

- Collect a large number of e-mails, gets users to label them.

| \$  | Hi  | CPSC | 340 | Vicodin | Offer | ... | Spam? |
|-----|-----|------|-----|---------|-------|-----|-------|
| 1   | 1   | 0    | 0   | 1       | 0     | ... | 1     |
| 0   | 0   | 0    | 0   | 1       | 1     | ... | 1     |
| 0   | 1   | 1    | 1   | 0       | 0     | ... | 0     |
| ... | ... | ...  | ... | ...     | ...   | ... | ...   |

- We can use ( $y_i = 1$ ) if e-mail ‘i’ is spam, ( $y_i = 0$ ) if e-mail is not spam.
- Extract features of each e-mail (like **bag of words**).
  - ( $x_{ij} = 1$ ) if word/phrase ‘j’ is in e-mail ‘i’, ( $x_{ij} = 0$ ) if it is not.

bonus!

# Feature Representation for Spam

- Are there better features than bag of words?
  - We add **bigrams** (sets of two words):
    - “CPSC 340”, “wait list”, “special deal”.
  - Or **trigrams** (sets of three words):
    - “Limited time offer”, “course registration deadline”, “you’re a winner”.
  - We might include the sender domain:
    - <sender domain == “mail.com”>.
  - We might include **regular expressions**:
    - <your first and last name>.

# Review of Supervised Learning Notation

- We have been using the notation 'X' and 'y' for supervised learning:



- X is matrix of all features, y is vector of all labels.
  - We use  $y_i$  for the label of example 'i' (element 'i' of 'y').
  - We use  $x_{ij}$  for feature 'j' of example 'i'.
  - We use  $x_i$  as the list of features of example 'i' (row 'i' of 'X').
    - So in the above  $x_3 = [0 \ 1 \ 1 \ 1 \ 0 \ 0 \ ...]$ .
    - In practice, only store list of non-zero features for each  $x_i$  (small memory requirement).

# Probabilistic Classifiers

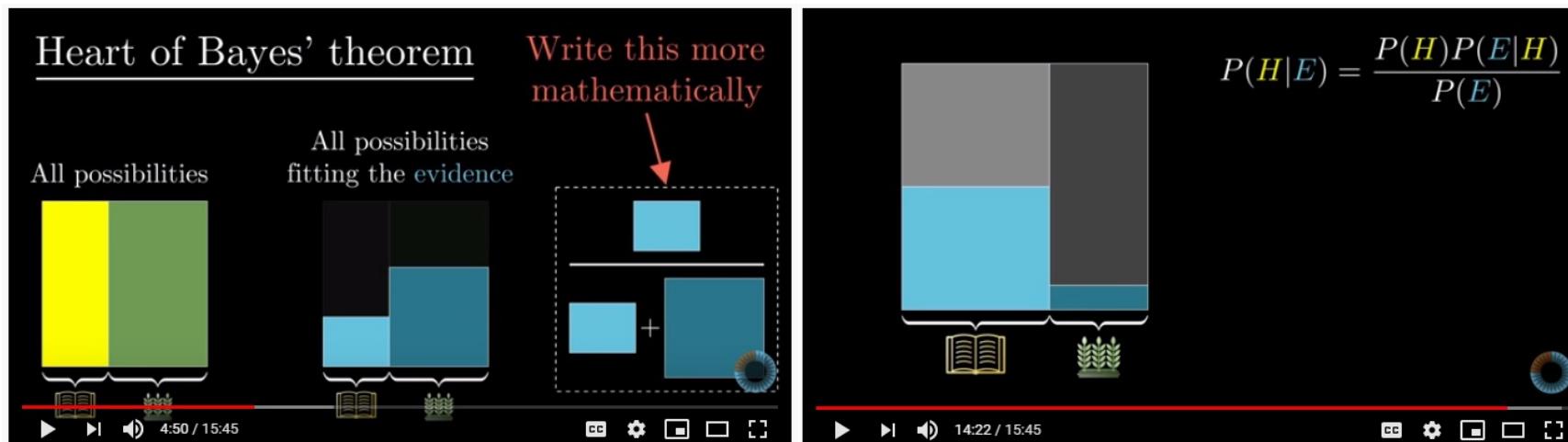
- For years, best spam filtering methods used naïve Bayes.
  - A probabilistic classifier based on Bayes rule.
  - It tends to work well with bag of words.
  - Recently shown to improve on state of the art for CRISPR “gene editing” ([link](#)).
- Probabilistic classifiers model the conditional probability,  $p(y_i | x_i)$ .
  - “If a message has words  $x_i$ , what is probability that message is spam?”
- Classify it as spam if probability of spam is higher than not spam:
  - If  $p(y_i = \text{"spam"} | x_i) > p(y_i = \text{"not spam"} | x_i)$ 
    - return “spam”.
  - Else
    - return “not spam”.

# Spam Filtering with Bayes Rule

- To model conditional probability, naïve Bayes uses Bayes rule:

$$p(y_i = \text{"spam"} | x_i) = \frac{p(x_i | y_i = \text{"spam"}) p(y_i = \text{"spam"})}{p(x_i)}$$

- Nice video giving visual intuition for Bayes rule [here](#):



# Spam Filtering with Bayes Rule

- To model conditional probability, naïve Bayes uses Bayes rule:

$$p(y_i = \text{"spam"} | x_i) = \frac{p(x_i | y_i = \text{"spam"}) p(y_i = \text{"spam"})}{p(x_i)}$$

- On the right we have three terms:
  - Marginal probability  $p(y_i)$  that an e-mail is spam.
  - Marginal probability  $p(x_i)$  that an e-mail has the set of words  $x_i$ .
  - Conditional probability  $p(x_i | y_i)$  that a spam e-mail has the words  $x_i$ .
    - And the same for non-spam e-mails.

# Spam Filtering with Bayes Rule

$$p(y_i = \text{"spam"} | x_i) = \frac{p(x_i | y_i = \text{"spam"}) p(y_i = \text{"spam"})}{p(x_i)}$$

- What do these terms mean?

ALL E-MAILS  
(including duplicates)

# Spam Filtering with Bayes Rule

$$p(y_i = \text{"spam"} | x_i) = \frac{p(x_i | y_i = \text{"spam"}) p(y_i = \text{"spam"})}{p(x_i)}$$

- $p(y_i = \text{"spam"})$  is probability that a random e-mail is spam.
  - This is **easy to approximate** from data: use the proportion in your data.



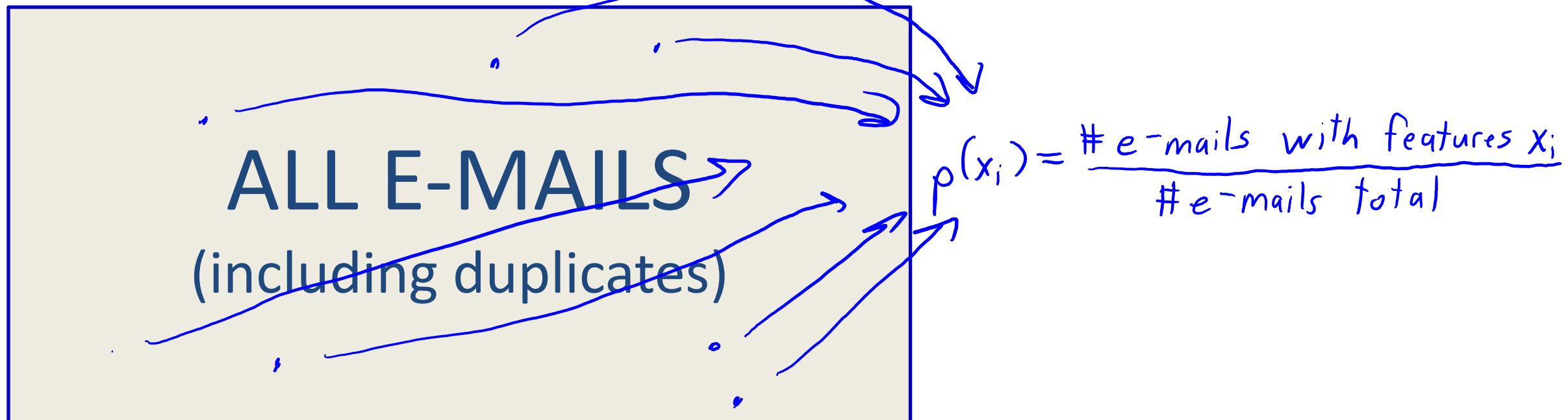
$$p(y_i = \text{"spam"}) = \frac{\# \text{spam messages}}{\# \text{total messages}}$$

This is an “estimate” of the true probability. In particular, this formula is a “**maximum likelihood estimate**” (MLE). We will cover likelihoods and MLEs later in the course.

# Spam Filtering with Bayes Rule

$$p(y_i = \text{"spam"} | x_i) = \frac{p(x_i | y_i = \text{"spam"}) p(y_i = \text{"spam"})}{p(x_i)}$$

- $p(x_i)$  is probability that a random e-mail has features  $x_i$ :
  - Hard to approximate: with ‘d’ words we need to collect  $2^d$  “coupons”, and that’s just to see each word combination once.



# Spam Filtering with Bayes Rule

$$p(y_i = \text{"spam"} | x_i) = \frac{p(x_i | y_i = \text{"spam"}) p(y_i = \text{"spam"})}{p(x_i)}$$

- $p(x_i)$  is probability that a random e-mail has features  $x_i$ :
  - Hard to approximate: with ‘d’ words we need to collect  $2^d$  “coupons”, but it turns out we can ignore it:

Naive Bayes returns “Spam” if  $p(y_i = \text{"spam"} | x_i) > p(y_i = \text{"not spam"} | x_i)$ .

By Bayes rule this means  $\frac{p(x_i | y_i = \text{"spam"}) p(y_i = \text{"spam"})}{p(x_i)} > \frac{p(x_i | y_i = \text{"not spam"}) p(y_i = \text{"not spam"})}{p(x_i)}$

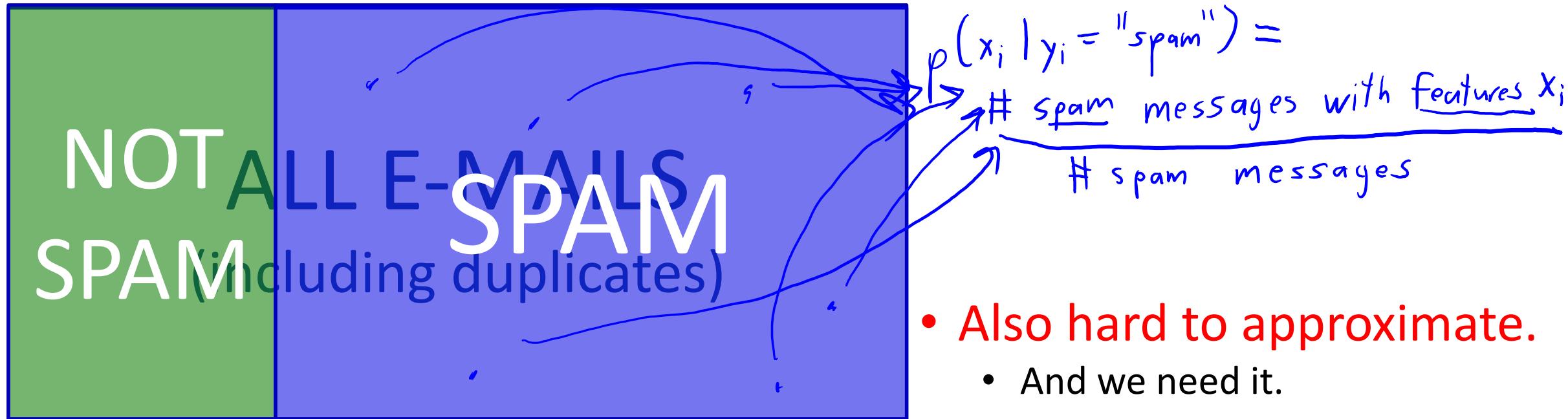
Multiply both sides by  $p(x_i)$ :

$$p(x_i | y_i = \text{"spam"}) p(y_i = \text{"spam"}) > p(x_i | y_i = \text{"not spam"}) p(y_i = \text{"not spam"})$$

# Spam Filtering with Bayes Rule

$$p(y_i = \text{"spam"} | x_i) = \frac{p(x_i | y_i = \text{"spam"}) p(y_i = \text{"spam"})}{p(x_i)}$$

- $p(x_i | y_i = \text{"spam"})$  is probability that spam has features  $x_i$ .



# Naïve Bayes

- Naïve Bayes makes a **big assumption** to make things easier:

$$p(\text{hello}=1, \text{vicodin}=0, 340=1 \mid \text{spam}) \approx p(\text{hello}=1 \mid \text{spam}) p(\text{vicodin}=0 \mid \text{spam}) p(340=1 \mid \text{spam})$$

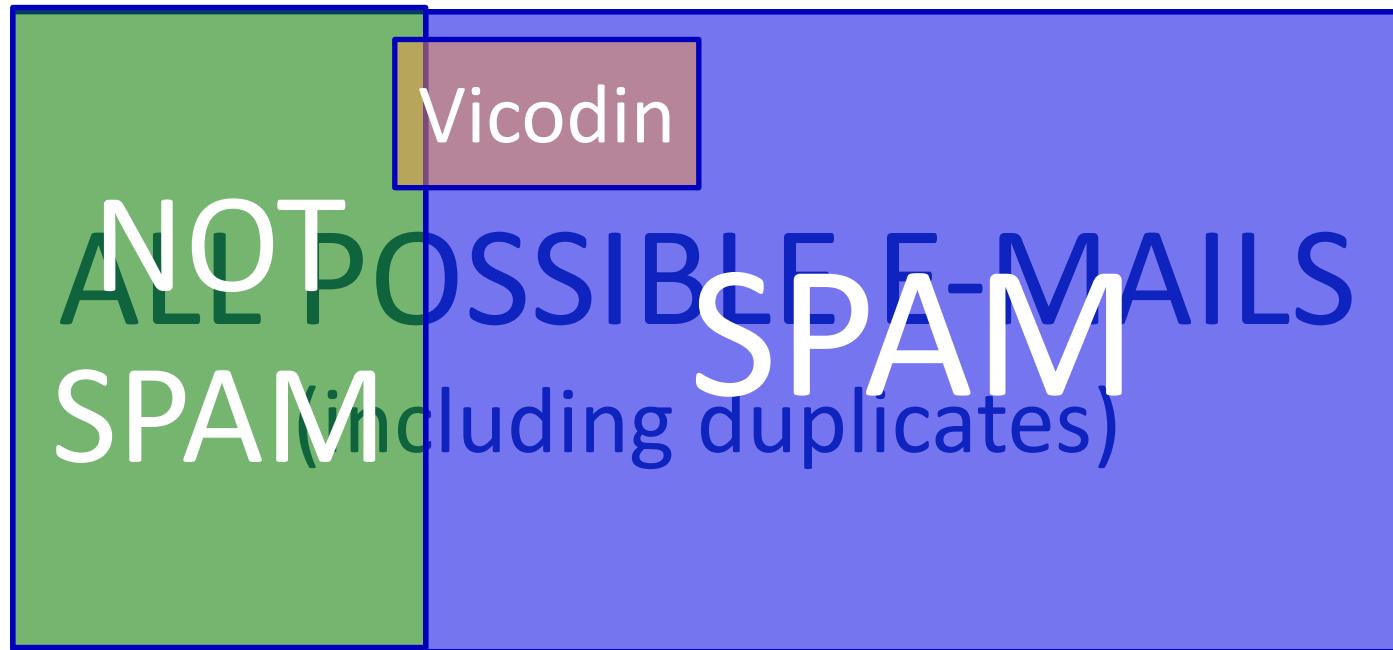
*HARD*

easy      easy      easy

- We assume *all* features  $x_i$  are **conditionally independent** given label  $y_i$ .
  - Once you know it's spam, probability of "vicodin" doesn't depend on "340".
  - *Definitely not true*, but sometimes a good approximation.
- And now we **only** need easy quantities like  $p(\text{"vicodin"} = 0 \mid y_i = \text{"spam"})$ .

# Naïve Bayes

- $p(\text{"vicodin"} = 1 \mid \text{"spam"} = 1)$  is probability of seeing “vicodin” in spam.

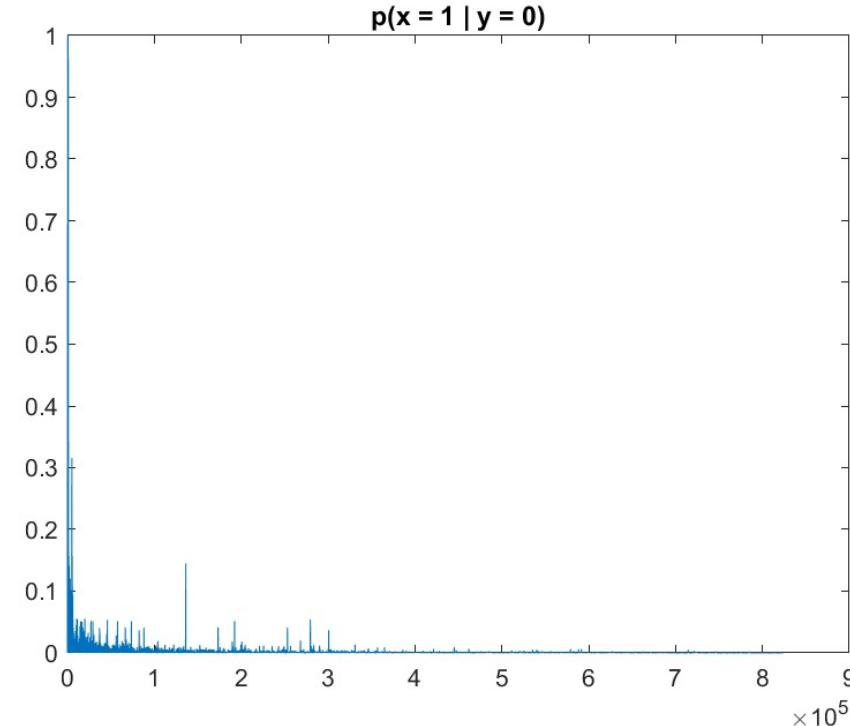
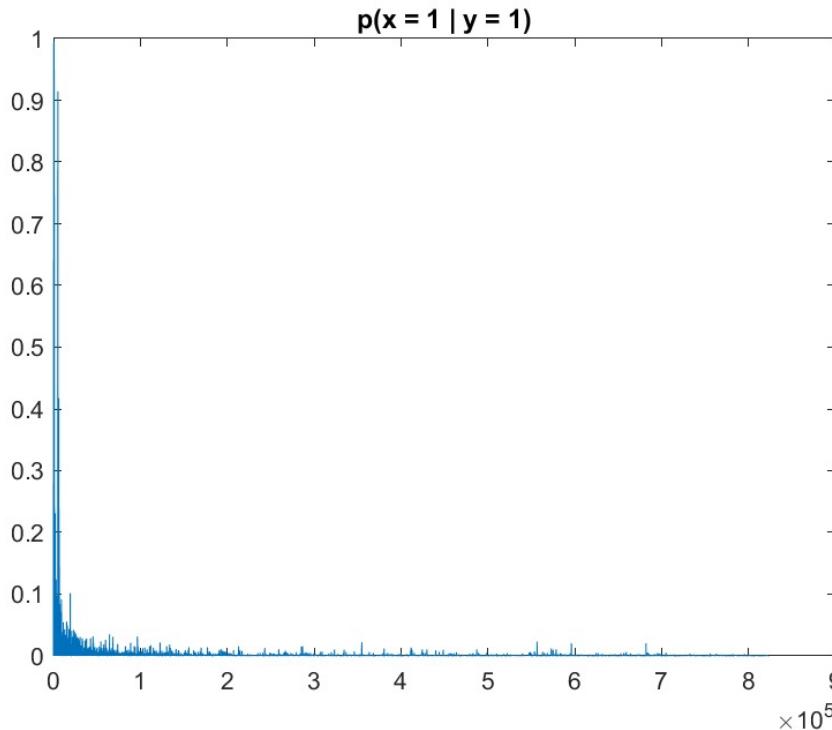


- Easy to estimate:  
$$p(\text{vicodin}=1 \mid \text{spam}=1) = \frac{\# \text{spam messages w/ vicodin}}{\# \text{spam messages}}$$

Again, this is a “maximum likelihood estimate” (MLE). We will cover how to derive this later.

# Naïve Bayes

- Comparing  $p(x \mid y = c)$  for “spam” and “not spam”:



- Even though independence is not true, these values may be enough to distinguish the classes.

# Summary

- Optimization bias: using a validation set too much overfits.
- Cross-validation: allows better use of data to estimate test error.
- No free lunch theorem: there is no “best” ML model.
- Probabilistic classifiers: try to estimate  $p(y_i \mid x_i)$ .
- Naïve Bayes: simple probabilistic classifier based on counting.
  - Uses conditional independence assumptions to make training practical.
- Next time:
  - A “best” machine learning model as ‘n’ goes to  $\infty$ .

bonus!

# Back to Decision Trees

- Instead of validation set, you can use CV to select tree depth.
- But you can also use these to decide **whether to split**:
  - Don't split if validation/CV error doesn't improve.
  - Different parts of the tree will have different depths.
- Or fit deep decision tree and **use [cross-]validation to prune**:
  - Remove leaf nodes that don't improve CV error.
- Popular implementations that have these tricks and others.

bonus!

# Random Subsamples

- Instead of splitting into  $k$ -folds, consider “random subsample” method:
  - At each “round”, choose a random set of size ‘ $m$ ’.
    - Train on all examples except these ‘ $m$ ’ examples.
    - Compute validation error on these ‘ $m$ ’ examples.
- Advantages:
  - Still an unbiased estimator of error.
  - Number of “rounds” does not need to be related to “ $n$ ”.
- Disadvantage:
  - Examples that are sampled more often get more “weight”.

bonus!

# Cross-Validation Theory

- Does CV give unbiased estimate of test error?
  - Yes!
    - Since each data point is only used once in validation, expected validation error on each data point is test error.
  - But again, if you use CV to select among models then it is no longer unbiased.
- What about variance of CV?
  - Hard to characterize.
  - CV variance on ‘n’ data points is worse than with a validation set of size ‘n’.
    - But we believe it is close.
- Does cross-validation remove optimization bias?
  - No, but the bias might be smaller since you have more “test” points.

bonus!

# Handling Data Sparsity

- Do we **need to store the full bag of words 0/1 variables?**
  - No: only need **list of non-zero features** for each e-mail.

| \$ | Hi | CPSC | 340 | Vicodin | Offer | ... |
|----|----|------|-----|---------|-------|-----|
| 1  | 1  | 0    | 0   | 1       | 0     | ... |
| 0  | 0  | 0    | 0   | 1       | 1     | ... |
| 0  | 1  | 1    | 1   | 0       | 0     | ... |
| 1  | 1  | 0    | 0   | 0       | 1     | ... |

VS.

| Non-Zeroes  |
|-------------|
| {1,2,5,...} |
| {5,6,...}   |
| {2,3,4,...} |
| {1,2,6,...} |

- Math/model doesn't change, but more efficient storage.

bonus!

# Generalization Error

- Usual measure of performance is the **generalization error**:
  - Average error for a random **new**  $(x, y)$  from the (hypothetical) data distribution.
  - “How well we expect to do on a *completely fresh* test set.”
- Test error vs. generalization error when labels are deterministic:

$$E_{\text{test}} = \mathbb{E} [ |\hat{y}^i - \tilde{y}^i| ]$$

↑ Labels are deterministic,  
but we still take  
expectation over data distribution.

$$E_{\text{generalize}} = \frac{1}{t} \sum_{\substack{i \\ x^i \notin \{\text{train}\} \\ \text{set}}} |\hat{y}_i - \tilde{y}_i|$$

↑ Number of  
 $x^i$  values not  
in training set.

Average error  
Over unseen  
 $x^i$  values.

# “Best” and the “Good” Machine Learning Models

bonus!

- Question 1: what is the “best” machine learning model?
  - The model that gets lower generalization error than all other models.
- Question 2: which models always do better than random guessing?
  - Models with lower generalization error than “predict 0” for all problems.
- No free lunch theorem:
  - There is no “best” model achieving the best generalization error for every problem.
  - If model A generalizes better to new data than model B on one dataset, there is another dataset where model B works better.

bonus!

# No Free Lunch Theorem

- Let's show the “no free lunch” theorem in a simple setting:
  - The  $x^i$  and  $y^i$  are binary, and  $y^i$  being a deterministic function of  $x^i$ .
- With ‘d’ features, each “learning problem” is a map from  $\{0,1\}^d \rightarrow \{0,1\}$ .
  - Assigning a binary label to each of the  $2^d$  feature combinations.

| Feature 1 | Feature 2 | Feature 3 |
|-----------|-----------|-----------|
| 0         | 0         | 0         |
| 0         | 0         | 1         |
| 0         | 1         | 0         |
| ...       | ...       | ...       |

| $y$ (map 1) | $y$ (map 2) | $y$ (map 3) | ... |
|-------------|-------------|-------------|-----|
| 0           | 1           | 0           | ... |
| 0           | 0           | 1           | ... |
| 0           | 0           | 0           | ... |
| ...         | ...         | ...         | ... |

- Let's pick one of these ‘y’ vectors (“maps” or “learning problems”) and:
  - Generate a set training set of ‘n’ IID samples.
  - Fit model A (convolutional neural network) and model B (naïve Bayes).

bonus!

# No Free Lunch Theorem

- Define the “unseen” examples as the  $(2^d - n)$  not seen in training.
  - Assuming no repetitions of  $x^i$  values, and  $n < 2^d$ .
  - Generalization error is the average error on these “unseen” examples.
- Suppose that model A got 1% error and model B got 60% error.
  - We want to show model B beats model A on another “learning problem”.
- Among our set of “learning problems” find the one where:
  - The labels  $y^i$  agree on all training examples.
  - The labels  $y^i$  disagree on all “unseen” examples.
- On this other “learning problem”:
  - Model A gets 99% error and model B gets 40% error.

bonus!

# Proof of No Free Lunch Theorem

- Let's show the “no free lunch” theorem in a simple setting:
  - The  $x^i$  and  $y^i$  are binary, and  $y^i$  being a deterministic function of  $x^i$ .
- With ‘d’ features, each “learning problem” is a map from each of the  $2^d$  feature combinations to 0 or 1:  $\{0,1\}^d \rightarrow \{0,1\}$

| Feature 1 | Feature 2 | Feature 3 |
|-----------|-----------|-----------|
| 0         | 0         | 0         |
| 0         | 0         | 1         |
| 0         | 1         | 0         |
| ...       | ...       | ...       |

| Map 1 | Map 2 | Map 3 | ... |
|-------|-------|-------|-----|
| 0     | 1     | 0     | ... |
| 0     | 0     | 1     | ... |
| 0     | 0     | 0     | ... |
| ...   | ...   | ...   | ... |

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bonus!

# Proof of No Free Lunch Theorem

- Further, across all “learning problems” with these ‘n’ examples:
  - Average generalization error of **every** model is 50% on unseen examples.
    - It’s right on each unseen example in exactly half the learning problems.
  - With ‘k’ classes, the average error is  $(k-1)/k$  (random guessing).
- This is kind of depressing:
  - For general problems, no “machine learning” is better than “predict 0”.
- But the proof also reveals the problem with the NFL theorem:
  - Assumes every “learning problem” is equally likely.
  - World encourages patterns like “similar features implies similar labels”.