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Prediction theory

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Outline

- Statistical model for binary outcomes
- ► Plug-in principle and IID model

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- Analysis of nearest neighbor classifier
- ► Estimating the error rate of a classifier
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Statistical model for binary outcomes

- Example: coin toss
- Physical model: hard

Assignation entropy in the leads probability $\theta \in [0,1]$ Help

- ► Encode heads as 1 and tails as 0
- ightharpoonup Written as $\operatorname{Bernoulli}(\theta)$
- https://pow/coder.comriable with
- ► Goal: correctly predict outcome

Optimal prediction

- ▶ Suppose $Y \sim \text{Bernoulli}(\theta)$.
- Assignment Project Exam Help
 - ► Indicator function notation:

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► The optimal prediction is incorrect with probability

Learning to make predictions

- ▶ If θ unknown:
- Assume we have data: outcomes of previous coin tosses

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Plug-in principle and IID model

- ► Plug-in principle:
- Assignment in Front extimate unknown(s) based on data (e.g., θ)

 Help
 - When can we estimate the unknowns?

 Notes and detailed the unknowns?

 Predict
 - ▶ <u>IID model</u>: Observations & (unseen) outcome are <u>iid</u> random

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Crucial modeling assumption that makes learning possible

▶ When is the IID assumption not reasonable? . . .

Statistical models

- ▶ Parametric statistical model $\{P_{\theta} : \theta \in \Theta\}$
- Assignment Parameterized probability distributions for data Assignment Parameter value & Exam Help
 - ▶ E.g., distributions on n binary outcomes treated as iid Bernoulli random variables,

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- Overload notation: P_{θ} is the <u>probability mass function</u> (<u>pmf</u>) for the distribution.
- Add We Chat powcoder $\{0,1\}^n$?

Maximum likelihood estimation (1)

- ightharpoonup Likelihood of parameter θ (given observed data)

Log-likelihood

htsometimes/more convenient oder are connenses in β som Vθ code of the paraceters in the same wav as $L(\theta)$

Maximum likelihood estimation (2)

- Coin toss example

Assignment Project Exam Help $\ln L(\theta) = \sum_{y_i \ln \theta + (1 - y_i) \ln(1 - \theta)} \text{Help}$

It Use calculus to determine formula for maximizer maximizer the is-a-little annoying, but someone else may already done it for you:

Back to plug-in principle

▶ We are given data $y_1, \ldots, y_n \in \{0, 1\}^n$, which we model using the IID model from before

the IID model from before Assigned find Properties Fixed means the IP properties of the Properties of the IID model from before the IID model from the II

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Analysis of the plug-in prediction (1)

- ► How good is the plug-in prediction?
 - ► Study behavior under the IID model, where

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- Y is the outcome to predict
- ightharpoonup heta is the unknown parameter

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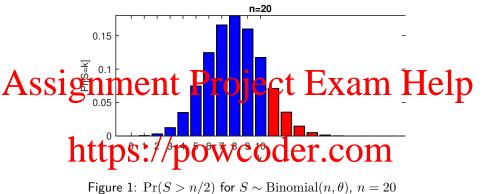
 $lackbox{ We cannot hope } \hat{Y}$ to beat this, but we can hope it is not much worse.

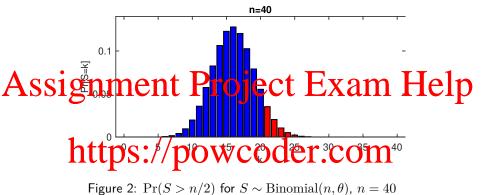
Analysis of the plug-in prediction (2)

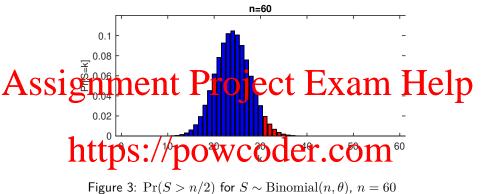
► Theorem:

 $\begin{array}{l} \mathbf{Assign}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}}. \\ \mathbf{Assign}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e^{-2n(\theta - 0.5)^2}. \\ \mathbf{Help}^{\Pr(\hat{Y} \neq Y) \leq \min\{\theta, 1-\theta\} + \frac{1}{2} \cdot |\theta - 0.5| \cdot e$

This probability is very small when n is large! $\begin{array}{c} \text{ This probability is very small when } n \text{ is large!} \\ \text{ the phase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ is large!} \\ \text{ biase } n \text{ the probability is very small when } n \text{ the probability is very small when } n \text{ the probability is very small when } n \text{ the probability is very small when } n \text{ the probability is very small when }$







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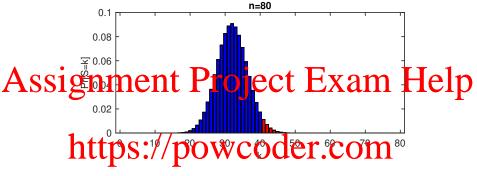


Figure 4: $\Pr(S > n/2)$ for $S \sim \text{Binomial}(n, \theta)$, n = 80

Statistical model for labeled data in binary classification

- ► Example: spam filtering
- ▶ Labeled example: $(x,y) \in \mathcal{X} \times \{0,1\}$
- Assignmente) Pare (the output (tapal) space p

 X is not necessarily the space of inputs itself (e.g., space of all

 emails), but rather the space of what we measure about inputs
 - We only see x (email), and then must make prediction of y
 - \blacktriangleright Statistical model: (X,Y) is random
 - ightharpoonup X has some marginal probability distribution

A Conditionary probability distribution of Y given X = tr is A Randulli with leads probability who WCOGET

 $\eta\colon\mathcal{X} o[0,1]$ is a function, sometimes called the regression function or conditional mean function (since $\overline{\mathbb{E}[Y\mid X=x]}=\eta(x)$).

Error rate of a classifier

▶ For a classifier $f: \mathcal{X} \to \{0, 1\}$, the <u>error rate</u> of f (with

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Recall that we had previously used the notation https://powcoder.com

which the same $\operatorname{Pr}(X) \not= \operatorname{Pr}(X)$ is uniform over the labeled examples in S.

 \triangleright Caution: This notation err(f) does not make explicit the dependence on (the distribution of) the random example (X,Y). You will need to determine this from context.

Conditional expectations (1)

- ► Consider any random variables *A* and *B*.
- ightharpoonup Conditional expectation of A given B:

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► Law of iterated expectations (a.k.a. tower property):

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Conditional expectations (2)

- Example: roll a fair 6-sided die
- Assign Harby from Personn facing up

 Assign Harb

Bayes classifier

Optimal classifier (Bayes classifier):

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where η is the conditional mean function

- Classifier with smallest probability of mistake
- Deptimal error rate (Bayes error rate):
- - Write error rate as $\operatorname{err}(f^{\star}) = \operatorname{Pr}(f^{\star}(X) \neq Y) = \mathbb{E}[\mathbf{1}_{\{f^{\star}(X) \neq Y\}}]$
 - Conditional on X, probability of mistake is

on (XW-ex) hat powcoder so, optimal error rate is

$$\begin{aligned} \operatorname{err}(f^{\star}) &= \mathbb{E}[\mathbf{1}_{\{f^{\star}(X) \neq Y\}}] \\ &= \mathbb{E}[\mathbb{E}[\mathbf{1}_{\{f^{\star}(X) \neq Y\}} \mid X]] \\ &= \mathbb{E}[\min\{\eta(X), 1 - \eta(X)\}]. \end{aligned}$$

Example: spam filtering

- ightharpoonup Suppose input x is a single (binary) feature, "is email all-caps?"
- ▶ How to interpret "the probability that email is spam given

Assignment Project Exam Help What does it mean for the Bayes classifier f* to be optimal?

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Learning prediction functions

- ▶ What to do if η is unknown?
- Assigned at the Parent System $(x_1,y_1),\ldots,(x_n,y_n)$ and $(x_1,y_1),\ldots,(x_n,y_n)$ for $i=1,\ldots,n$. Help
 - ▶ IID model: $Z_1, ..., Z_n, Z$ are iid random variables
 - $Z=(X,Y) \text{ is the (unseen) "test" example } \\ \text{Technically, each labeled example is a } \\ \mathcal{X} \times \{0,1\} \text{ valued range on variable.} \\ \text{random variables.} \\ \text{}$

Performance of nearest neighbor classifier

- Study in context of IID model
- Assume $\eta(x) \approx \eta(x')$ whenever x and x' are close.

Assignish Europe the probling assumption Examination of the problem of the proble

- Let (X,Y) be the "test" example, and suppose $(X_{\hat{i}},Y_{\hat{i}})$ is the nearest neighbor among training data
- For large n, X and $X_{\hat{i}}$ likely to be close enough so that $\eta(X) \approx \eta(X_{\hat{i}})$.
- Prediction is Y₂, true label is Y.
- $\begin{array}{c|c} \blacktriangleright & \text{ cold} & \text{ cold}$
- ► Conclusion: expected error rate is

 $\mathbb{E}[\operatorname{err}(\operatorname{NN}_S)] \approx 2 \cdot \mathbb{E}[\eta(X)(1 - \eta(X))]$ for large n

- ▶ Recall that optimal is $\mathbb{E}[\min\{\eta(X), 1 \eta(X)\}]$.
- ▶ So $\mathbb{E}[\operatorname{err}(\operatorname{NN}_S)]$ is at most twice optimal.
- Never exactly optimal unless $\eta(x) \in \{0,1\}$ for all x.

Test error rate (1)

- How to estimate error rate?
- ► IID model:

Assignment Y_1 Project (X_2, X_3) Hielp

- Test examples (that you have): $(X'_1, Y'_1), \dots, (X'_m, Y'_m)$
- Test example (that you don't have) used to define error rate:

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- ightharpoonup Classifier f is based only on training examples
- Hence, test examples are independent of \hat{f} (very important)
- ► WevaldliketVerCathat powcoder
 - ► Caution: since \hat{f} depends on training data, it is random!
 - ► Convention: When we write $\operatorname{err}(\hat{f})$ where \hat{f} is random, we really mean $\operatorname{Pr}(\hat{f}(X) \neq Y \mid \hat{f})$.
 - ▶ Therefore $err(\hat{f})$ is a random variable!

Test error rate (2)

▶ Conditional distribution of $S := \sum_{i=1}^m \mathbf{1}_{\{\hat{f}(X_i') \neq Y_i'\}}$ given training data:

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► Therefore, test error rate

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is close to ε when m is large

- How accurate is the estimate? Depends on the (conditional) variance!
 - $ightharpoonup \operatorname{var}(rac{1}{m}S\mid\operatorname{training\ data}) = rac{arepsilon(1-arepsilon)}{m}$
 - Standard deviation is $\sqrt{\frac{\varepsilon(1-\varepsilon)}{m}}$

Confusion tables

- ► True positive rate (recall): $Pr(f(X) = 1 \mid Y = 1)$

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Confusion table

```
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y = 0 # true negatives # false positives
           y = 1 \parallel \# false negatives \parallel \# true positives
```

ROC curves

- ► Receiver operating characteristic (ROC) curve

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 $Add \stackrel{\text{Figure 5: TPR vs FPR plot with two points}}{WeChat} powcoder$

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 $Add \stackrel{\text{Figure 6: TPR vs FPR plot with many points}}{WeChat} \\ powcoder$

More than two outcomes

- ▶ What if there are K > 2 possible outcomes?
- ightharpoonup Replace coin with K-sided die

Assigning probability vector $\theta = (\theta_1, \dots, \theta_K)$

- $\blacktriangleright \ \theta_k \geq 0$ for all $k \in [K]$, and $\sum_{k=1}^K \theta_k = 1$
- ► https://pow.coder.com

Statistical model for multi-class classification

 \triangleright Statistical model for labeled examples (X,Y), where Y takes values in [K]

- Conditional probability function: $\eta(x)_k := \Pr(Y = k \mid X = x)$

Optimal classifier: $f^*(x) = \arg\max_{k \in [K]} \eta(x)_k$

Potential downsides of the IID model

handwriting, but eventually use on digits written by Bob.

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Matdide wat teer that use and gifts, written by both Alice and Bob!