Week 2 Video 1

Detector Confidence
Classification

- There is something you want to predict ("the label")
- The thing you want to predict is categorical
It can be useful to know yes or no
It can be useful to know yes or no

- The detector says you don’t have Ptarmigan’s Disease!
It can be useful to know yes or no

- But it’s even more useful to know how certain the prediction is
It can be useful to know yes or no

- But it’s even more useful to know how certain the prediction is
  - The detector says there is a 50.1% chance that you don’t have Ptarmigan’s disease!
Uses of detector confidence
Uses of detector confidence

- Gradated intervention
  - Give a strong intervention if confidence over 60%
  - Give no intervention if confidence under 60%
  - Give “fail-soft” intervention if confidence 40-60%
Uses of detector confidence

- Decisions about strength of intervention can be made based on cost-benefit analysis
- What is the cost of an incorrectly applied intervention?
- What is the benefit of a correctly applied intervention?
Example

- An incorrectly applied intervention will cost the student 1 minute
- Each minute the student typically will learn 0.05% of course content
- A correctly applied intervention will result in the student learning 0.03% more course content than they would have learned otherwise
Expected Value of Intervention

\[ 0.03 \times \text{Confidence} - 0.05 \times (1 - \text{Confidence}) \]
Adding a second intervention

\[ 0.05 \times \text{Confidence} - 0.08 \times (1 - \text{Confidence}) \]
Intervention cut-points
Uses of detector confidence
Uses of detector confidence

- Discovery with models analyses
  - When you use this model in further analyses
  - We’ll discuss this later in the course
  - Big idea: keep all of your information around
Not always available

- Not all classifiers provide confidence estimates
Not always available

- Not all classifiers provide confidence estimates

- Some, like step regression, provide pseudo-confidences
  - do not scale nicely from 0 to 1
  - but still show relative strength that can be used in comparing two predictions to each other
Some algorithms give it to you in straightforward fashion

- “Confidence = 72%”
With others, you need to parse it out of software output

Tree

```
a > 1.174: Y {N=0, Y=47}
a ≤ 1.174
  |   d > 1.491: Y {N=0, Y=2}
  |   d ≤ 1.491
  |   |   d > 1.431: Y {N=1, Y=2}
  |   |   d ≤ 1.431
  |   |   |   day > 8.500: Y {N=1, Y=1}
  |   |   |   day ≤ 8.500: N {N=44, Y=1}
```
With others, you need to parse it out of software output

\[
C = \frac{Y}{Y+N}
\]
With others, you need to parse it out of software output.

\[
C = \frac{2}{2+1}
\]
With others, you need to parse it out of software output

**Tree**

\[
\begin{align*}
a &> 1.174: Y \{N=0, Y=47\} \\
a &\leq 1.174 \\
\quad &d > 1.491: Y \{N=0, Y=2\} \\
\quad &d \leq 1.491 \\
\quad \quad &d > 1.431: Y \{N=1, Y=2\} \\
\quad \quad &d \leq 1.431 \\
\quad \quad \quad &\text{day} > 8.500: Y \{N=1, Y=1\} \\
\quad \quad \quad &\text{day} \leq 8.500: N \{N=44, Y=1\}
\end{align*}
\]

\[C = 66.6667\%\]
With others, you need to parse it out of software output

Tree

\[
\begin{align*}
a > 1.174: & \ Y \ \{N=0, \ Y=47\} \\
a \leq 1.174: & \\
& \mid d > 1.491: \ Y \ \{N=0, \ Y=2\} \\
& \mid d \leq 1.491: \\
& \quad \mid d > 1.431: \ Y \ \{N=1, \ Y=2\} \\
& \quad \mid d \leq 1.431: \\
& \quad \quad \mid \text{day} > 8.500: \ Y \ \{N=1, \ Y=1\} \\
& \quad \quad \mid \text{day} \leq 8.500: \ N \ \{N=44, \ Y=1\}
\end{align*}
\]
With others, you need to parse it out of software output

Tree

\[
\begin{align*}
a > 1.174 & \Rightarrow Y \{N=0, \; Y=47\} \\
a \leq 1.174 & \\
\quad & | \quad d > 1.491 \Rightarrow Y \{N=0, \; Y=2\} \\
\quad & | \quad d \leq 1.491 \\
\quad & \quad | \quad d > 1.431 \Rightarrow Y \{N=1, \; Y=2\} \\
\quad & \quad | \quad d \leq 1.431 \\
\quad & \quad \quad | \quad day > 8.500 \Rightarrow Y \{N=1, \; Y=1\} \\
\quad & \quad \quad | \quad day \leq 8.500 \Rightarrow N \{N=44, \; Y=1\}
\end{align*}
\]
With others, you need to parse it out of software output

\[
\text{Tree}
\]

\[
a > 1.174: \ Y \ {\{N=0, \ Y=47\}}
\]
\[
a \leq 1.174
\]
\[
| \quad d > 1.491: \ Y \ {\{N=0, \ Y=2\}}
\]
\[
| \quad d \leq 1.491
\]
\[
| \quad | \quad d > 1.431: \ Y \ {\{N=1, \ Y=2\}}
\]
\[
| \quad | \quad d \leq 1.431
\]
\[
| \quad | \quad | \quad \text{day} > 8.500: \ Y \ {\{N=1, \ Y=1\}}
\]
\[
| \quad | \quad | \quad \text{day} \leq 8.500: \ N \ {\{N=44, \ Y=1\}}
\]

C = 2.22%
(or NO with 97.88%)
Confidence can be “lumpy”

- Previous tree only had values
  - 100%, 66.67%, 50%, 2.22%

- This isn’t a problem per-se
  - But some implementations of standard metrics (like $A'$) can behave oddly in this case
  - We’ll discuss this later this week

- Common in tree and rule based classifiers
Confidence

- Almost always a good idea to use it when it’s available
- Not all metrics use it, we’ll discuss this later this week
Risk Ratio

- A good way of analyzing the impact of specific predictors on your prediction

- Not available through all tools
Risk Ratio

- Used with binary predictors

- Take predictor $P$

$$RR = \frac{\text{Probability when } P = 1}{\text{Probability when } P = 0}$$
Risk Ratio: Example

- Students who get into 3 or more fights in school have a 20% chance of dropping out.

- Students who do not get into 3 or more fights in school have a 5% chance of dropping out.

\[ RR = \frac{\text{Probability when } 3\text{Fights}=1}{\text{Probability when } 3\text{Fights}=0} = \frac{0.2}{0.05} = 4 \]

- The Risk Ratio for 3+ fights is 4.
- You are 4 times more likely to drop out if you get into 3 or more fights in school.
Risk Ratio: Notes

- You can turn numerical predictors into binary predictors with a threshold
  - Like our last example!

- Clear way to communicate the effects of a variable on your predicted outcome
Thanks!