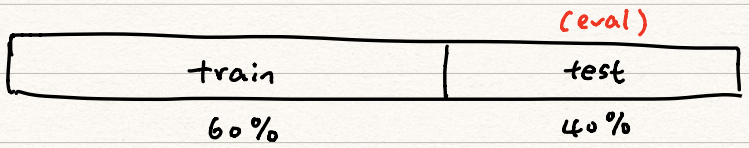
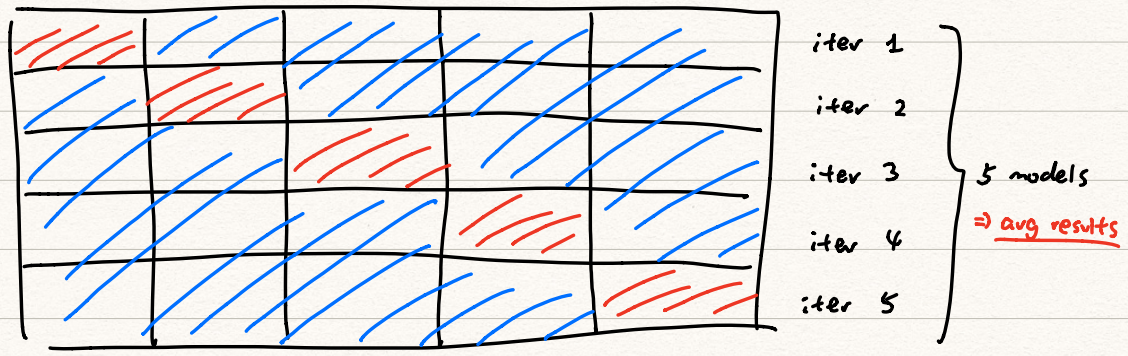
1. How is **holdout** evaluation different to **cross-validation** evaluation? What are some reasons we would prefer one strategy over the other?

Hold-out : fixed



subject to some random variation in allocation of instances (to train & test)

Cross-validation : K-fold (K=5 partitions)



for test

for train

Each instance is used for testing.
(But CV takes longer)

2. A **confusion matrix** is a summary of the performance of a (supervised) classifier over a set of development ("test") data, by counting the various instances:

		Actual			
		a	*b*	*c*	*d*
Classified	*a*	10	2	3	1
	b	2	5	3	1
	c	1	3	7	1
	d	3	0	3	5

(i). Calculate the classification **accuracy** of the system. Find the **error rate** for the system.

$$\text{Acc} = \frac{\#\text{ of correctly classified}}{\text{total \# of instances}}$$

$$= \frac{10+5+7+5}{\text{sum of the table}} = \frac{27}{50}$$

$$= 54\%$$

$$\text{ER} = 1 - \text{Acc} = 47\%$$

(ii). Calculate the **precision**, **recall** and **F-score** (where $\beta = 1$) for class *d*.

$$\text{Precision} = \frac{\#\text{ of instances "correctly" classified as } d}{\#\text{ of instances classified as } d} = \frac{TP}{TP+FP} = \frac{5}{5+6} = \frac{5}{11}$$

$$\text{Recall} = \frac{\#\text{ of instances "correctly" classified as } d}{\#\text{ of instances truly } d} = \frac{TP}{TP+FN} = \frac{5}{5+3} = \frac{5}{8}$$

		Actual			
		a	*b*	*c*	*d*
Classified	*a*	10	2	3	1
	b	2	5	3	1
	c	1	3	7	1
	d	3	0	3	5

FN = 3 (*a*, *b*, *c* rows, *d* column); FP = 6 (*d* row, *a*, *b*, *c* columns); TP = 5 (*d* row, *d* column)

$$\beta = 1 : F_1 = \frac{2PR}{P+R} = \frac{2}{\frac{1}{P}+\frac{1}{R}} \quad \text{(harmonic mean)}$$

$$= \frac{2 \cdot \frac{5}{11} \cdot \frac{5}{8}}{\frac{5}{11}+\frac{5}{8}}$$

$$= 53\%$$

(iii). Why can't we do this for the whole system? How can we consider the whole system?

Why:

precision & recall: defined per-class (interesting class v.s. the rest)

How:

1. Calculate precision & recall for each class
2. Take average (e.g. Macro, Micro, Weighted Averaging)

emphasize small classes — large classes

3. For the following dataset:

ID	*Outl*	*Temp*	*Humi*	*Wind*	PLAY
TRAINING INSTANCES					
A	s	h	h	F	N
B	s	h	h	T	N
C	o	h	h	F	Y
D	r	m	h	F	Y
E	r	c	n	F	Y
F	r	c	n	T	N
TEST INSTANCES					
G	o	c	n	T	?
H	s	m	h	F	?

(i). Classify the test instances using the method of **0-R**.

0-R: Majority class classifier

train: 3Y, 3N (choose either!)

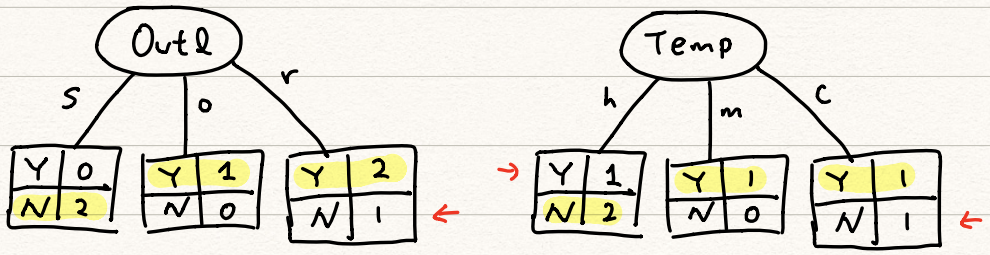
⇒ Let's choose "N"

⇒ Instances: G → N

H → N

(ii). Classify the test instances using the method of **1-R**. (for H assume *Outl = s*)

1 - R: Classify instances based on one attribute



$ER = \frac{1}{6}$ $ER = \frac{2}{6}$

Choose attribute with lowest ER: Assume "Outl" is best

⇒ Instances: G: Outl = o → Y

H: Outl = s → N

ID	*Outl*	*Temp*	*Humi*	*Wind*	PLAY
TRAINING INSTANCES					
A	s	h	n	F	N
B	s	h	h	T	N
C	o	h	h	F	Y
D	r	m	h	F	Y
E	r	c	n	F	Y
F	r	c	n	T	N
TEST INSTANCES					
G	o	m	n	T	?
H	?	h	?	F	?

4. Given the above dataset, we wished to perform feature selection on this dataset, where the class is PLAY:

(i). Which of `Humi` and `Wind` has the greatest *Pointwise Mutual Information* for the class Y? What about N?

PMI:

$$PMI(A,C) = \log_2 \frac{P(A,C)}{P(A)\,P(C)}$$ ⇒ find A with largest PMI

$\frac{P(A,C)}{P(A)P(C)} \sim 1$ ⇒ Independent

$\ll 1$ ⇒ Negatively correlated

✡ $\gg 1$ ⇒ occur together (positively correlated, if one occur, the other likely to occur)

For (A) Humi & (C) Y: (let Humi : h:T)

$$PMI(Humi=h, Play=Y) = \log_2 \frac{\frac{2}{6}}{\frac{4}{6}\cdot\frac{3}{6}} = \log_2 1 = 0 \quad \text{(uncorrelated)}$$

For (A) Wind & (C) Y:

$$PMI(Wind=T, Play=Y) = \log_2 \frac{\frac{0}{6}}{\frac{2}{6}\,\frac{3}{6}} = \log_2 0 = -\infty \quad \text{(neg correlated)}$$

⇒ Humi has better PMI for class Y.

Neg class (N):

Humi: still uncorrelated

Wind: pos correlated

(per-class)

(ii). Which of the attributes has the greatest *Mutual Information* for the class, as a whole?

4 terms

$$MI(A,C) = \underbrace{\sum_{i\in\{a,\bar{a}\}} \sum_{j\in\{c,\bar{c}\}} P(i,j)}_{\text{weighted-avg}} \underbrace{\log_2 \frac{P(i,j)}{P(i)\,P(j)}}_{\text{PMI}}$$

$$\Rightarrow MI(A,C) = \sum_{i\in A} \sum_{j\in\{c,\bar{c}\}} P(i,j) \log_2 \frac{P(i,j)}{P(i)\,P(j)}$$

↑ all values

MI: Combine PMIs of the attribute occurring together with each class, as well as not occurring.

For (a) Outl & (c) Play:

$$MI(Outl, Play) = P(s,Y)\log_2\frac{P(s,Y)}{P(s)P(Y)} + P(o,Y)\log_2\frac{P(o,Y)}{P(o)P(Y)} + P(r,Y)\log_2\frac{P(r,Y)}{P(r)P(Y)} + P(s,N)\log_2\frac{P(s,N)}{P(s)P(N)} + P(o,N)\log_2\frac{P(o,N)}{P(o)P(N)} + P(r,N)\log_2\frac{P(r,N)}{P(r)P(N)}$$

MI(Outl)

$$= \frac{0}{6}\log_2\frac{\frac{0}{6}}{\frac{3}{6}\cdot\frac{3}{6}} + \frac{1}{6}\log_2\frac{\frac{1}{6}}{\frac{1}{6}\cdot\frac{3}{6}} + \cdots$$

$$= 0.541$$

For (a) Temp & (c) Play:

$$MI(Temp, Play) = P(h,Y)\log_2\frac{P(h,Y)}{P(h)P(Y)} + P(h,N)\log_2\frac{P(h,Y)}{P(h)P(Y)} + P(m,Y)\log_2\frac{P(m,Y)}{P(m)P(Y)} + P(m,N)\log_2\frac{P(m,N)}{P(m)P(N)} + P(c,Y)\log_2\frac{P(c,N)}{P(c)P(N)} + P(c,N)\log_2\frac{P(c,N)}{P(c)P(N)}$$

MI(Temp)

$$= 0.110$$

For (a) Humi & (c) Play : MI = 0

For (a) Wind & (c) Play : MI = 0.459

} exercise

⇒ Outl is the best attribute (MI)

PMI : attribute value & a class value (c or $\bar{c}$)

MI : an attribute (consider all values) & a class (c & $\bar{c}$)