Introduction to Data Science (IDS) course

Responsible Data Science

Lecture 20 and 21 Instruction

IDS-L20-L21

Chair of Process and Data Science

RWTH AACHEN UNIVERSITY

Discrimination

Consider the following potentially discriminatory and the base rules, with the mentioned confidence values.
What range for α causes these rules to be discriminatory?

Base Rule	$B \Rightarrow C$	**Confidence: 0.25**
PD Rule	$A, B \Rightarrow C$	**Confidence: 0.55**

Discrimination

Consider the following potentially discriminatory and the base rules, with the mentioned confidence values.
What range for α causes these rules to be discriminatory?

Base Rule	$B \Rightarrow C$	**Confidence: 0.25**
PD Rule	$A, B \Rightarrow C$	**Confidence: 0.55**

$$elift = \frac{confidence(A, B \Rightarrow C)}{confidence(B \Rightarrow C)} \qquad elift = \frac{0.55}{0.25} = 2.2$$

If $\alpha \leq 2.2$, then the rule is discriminatory.

Discrimination (Your Turn)

Consider the following potentially discriminatory and the base rules, with the mentioned support values.
What range for α causes these rules to be discriminatory?

Base Rule	$\boldsymbol{B \Rightarrow C}$	$\boldsymbol{Support(\{B, C\}): 30}$	$\boldsymbol{Support(\{B\}): 100}$
PD Rule	$\boldsymbol{A, B \Rightarrow C}$	$\boldsymbol{Support(\{A, B, C\}): 20}$	$\boldsymbol{Support(\{A, B\}): 40}$

Discrimination (Solution)

Consider the following potentially discriminatory and the base rules, with the mentioned support values.
What range for α causes these rules to be discriminatory?

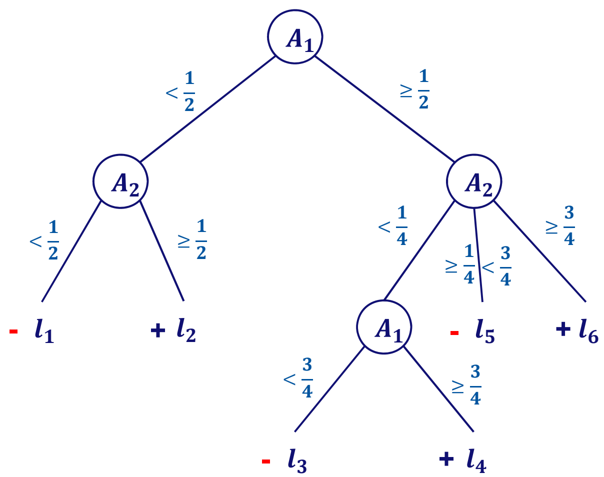
Base Rule	$B \Rightarrow C$	$Support(\{B, C\}): 30$	$Support(\{B\}): 100$
PD Rule	$A, B \Rightarrow C$	$Support(\{A, B, C\}): 20$	$Support(\{A, B\}): 40$

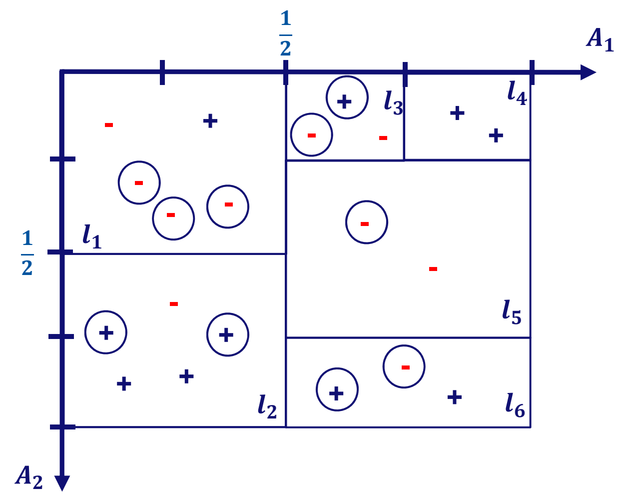
$$elift = \frac{confidence(A, B \Rightarrow C)}{confidence(B \Rightarrow C)}$$

$$elift = \frac{\frac{support(\{A,B,C\})}{support(\{A,B\})}}{\frac{support(\{B,C\})}{confidence(\{B\})}} = \frac{\frac{20}{40}}{\frac{30}{100}} = 1.6$$

If α ≤ 1.6, then the rule is discriminatory.

Discrimination





1. **Classify the regions based on their majority label.**
2. **Compute the accuracy and also the discrimination of the classifier w.r.t. discriminatory attribute (B).**
3. **If we want to relabel l_1, what would be the new label? and how this relabeling would affect the accuracy and discrimination?**

Note that encircled examples are discriminatory (have B=1).

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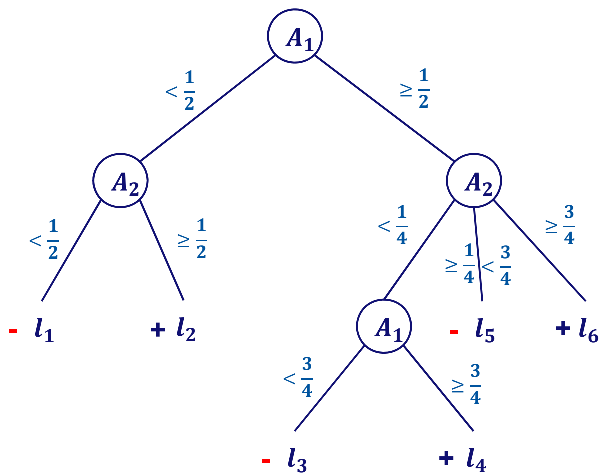
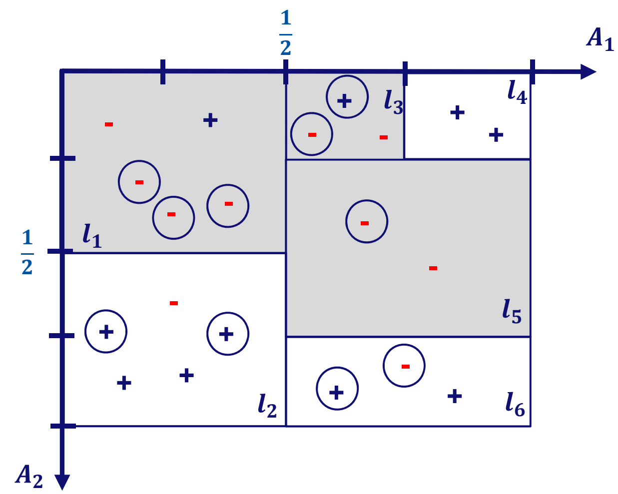
Discrimination

1. Classify the regions based on their majority label.





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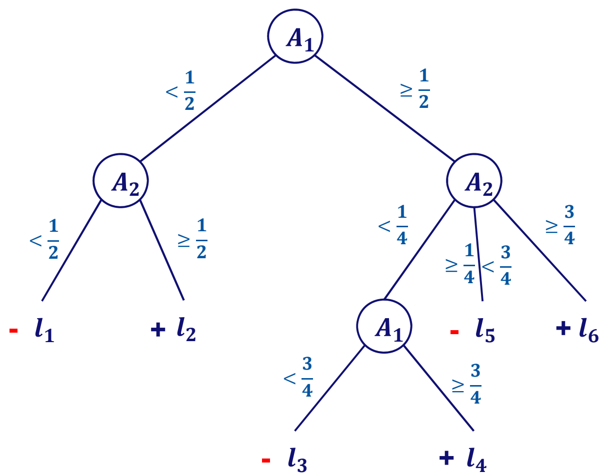
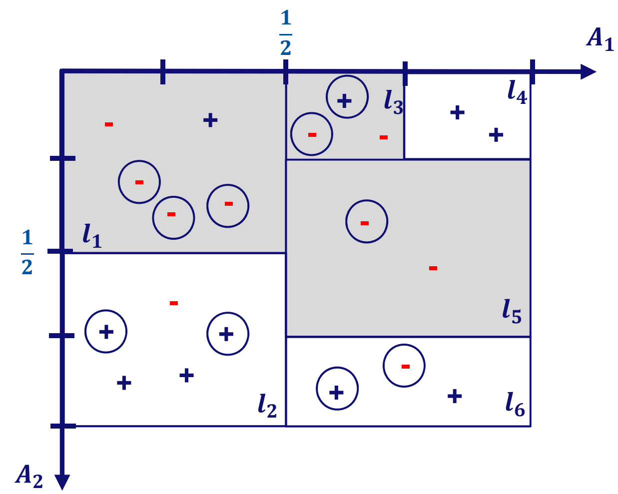
Discrimination

2. Compute the accuracy and also the discrimination of the classifier w.r.t. discriminatory attribute (B).





Class	-	+	
Pred.	- / +	- / +	
$B = 1$	U_1/U_2	V_1/V_2	b
$B = 0$	W_1/W_2	X_1/X_2	$\bar{b}$
	N_1/N_2	P_1/P_2	1

Class	-	+	
Pred.	- / +	- / +	
$B = 1$	$\frac{5}{20} / \frac{1}{20}$	$\frac{1}{20} / \frac{3}{20}$	$\frac{10}{20}$
$B = 0$	$\frac{3}{20} / \frac{1}{20}$	$\frac{1}{20} / \frac{5}{20}$	$\frac{10}{20}$
	$\frac{8}{20} / \frac{2}{20}$	$\frac{2}{20} / \frac{8}{20}$	1

$$acc_T = N_1 + P_2 = \frac{8}{20} + \frac{8}{20} = 0.8$$

$$disc_T = \frac{W_2 + X_2}{\bar{b}} - \frac{U_2 + V_2}{b} = \frac{\frac{1}{20} + \frac{5}{20}}{\frac{1}{2}} - \frac{\frac{1}{20} + \frac{3}{20}}{\frac{1}{2}} = 0.2$$

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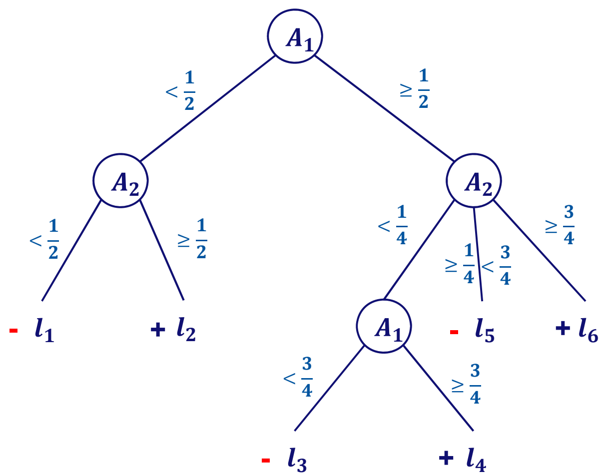
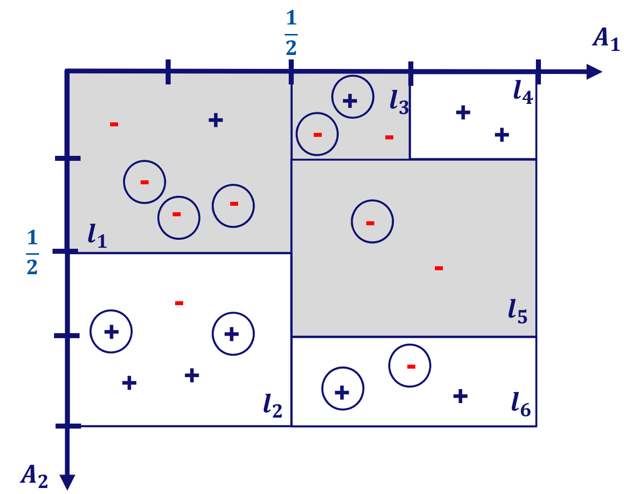
Discrimination

3. If we want to relabel l_1, what would be the new label? and how this relabeling would affect the accuracy and discrimination?





Class	-	+	
$B=1$	u	v	b
$B=0$	w	x	$\bar{b}$
	n	p	a

Class	-	+	
$B=1$	3/20	0	3/20
$B=0$	1/20	1/20	2/20
	4/20	1/20	5/20

$$n > p$$

New label would be +

$$\Delta acc_l = p - n = -3/20$$

$$\Delta disc_l = -\frac{u+v}{b} + \frac{w+x}{\bar{b}} = -\frac{\frac{3}{20}}{\frac{1}{2}} + \frac{\frac{2}{20}}{\frac{1}{2}} = -0.1$$

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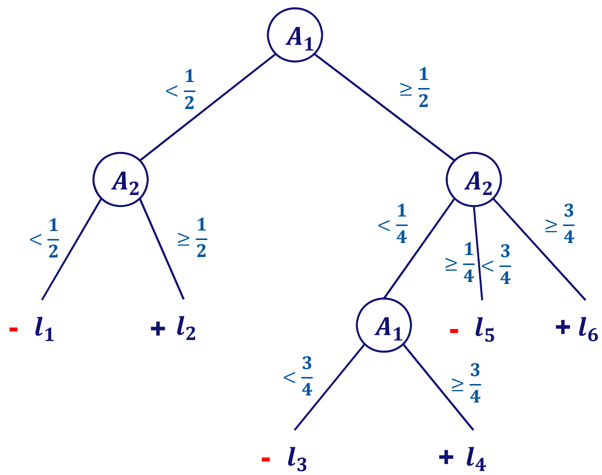
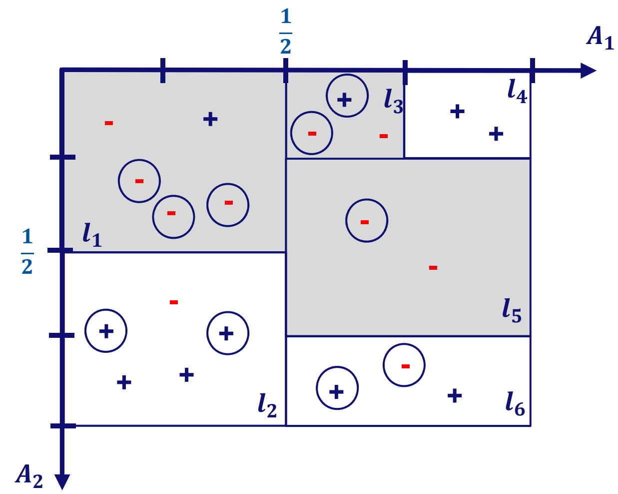
Discrimination

If we want to relabel l_6, what would be the new label? and how this relabeling would affect the accuracy and discrimination?





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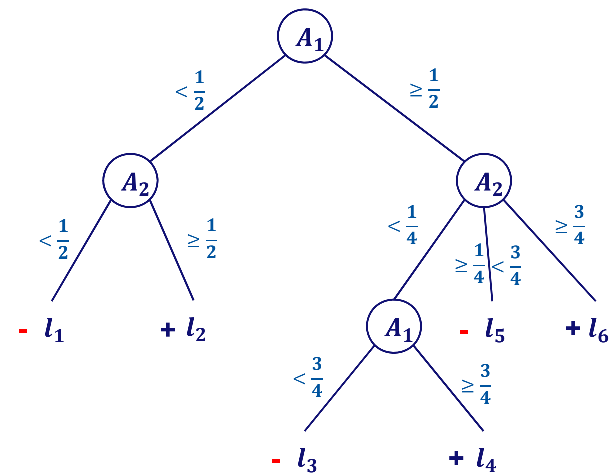
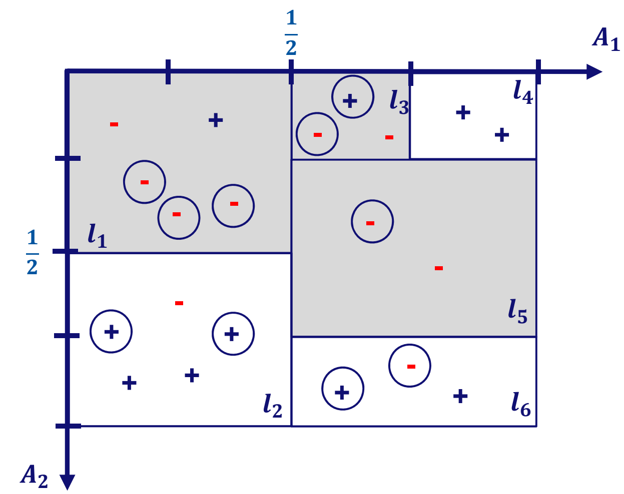
Discrimination

If we want to relabel l_6, what would be the new label? and how this relabeling would affect the accuracy and discrimination?





Class	-	+	
$B = 1$	u	v	b
$B = 0$	w	x	$\bar{b}$
	n	p	a

Class	-	+	
$B = 1$	$1/20$	$1/20$	$2/20$
$B = 0$	0	$1/20$	$1/20$
	$1/20$	$2/20$	$3/20$

$$n < p$$

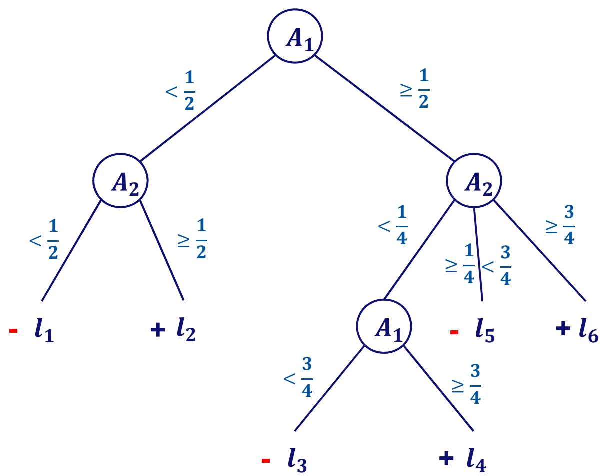
New label would be -

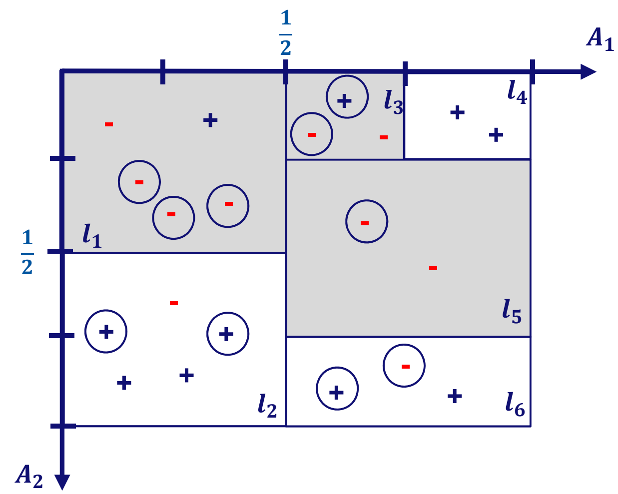
$$\Delta acc_l = n - p = -1/20$$

$$\Delta disc_l = \frac{u+v}{b} - \frac{w+x}{\bar{b}} = \frac{\frac{2}{20}}{\frac{1}{2}} - \frac{\frac{1}{20}}{\frac{1}{2}} = 0.1$$

Discrimination (Your Turn)

If we want to relabel l_4, what would be the new label? and how this relabeling would affect the accuracy and discrimination?





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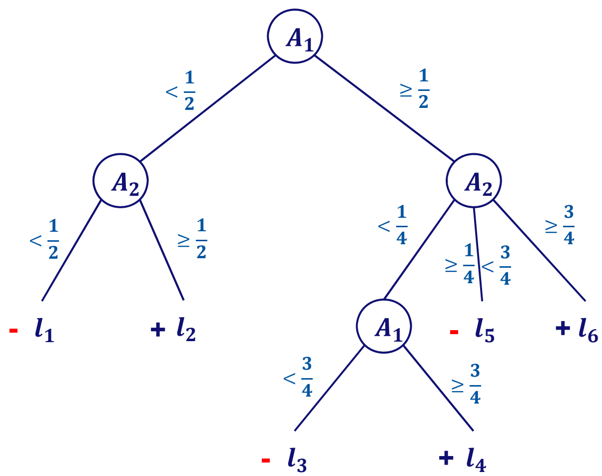
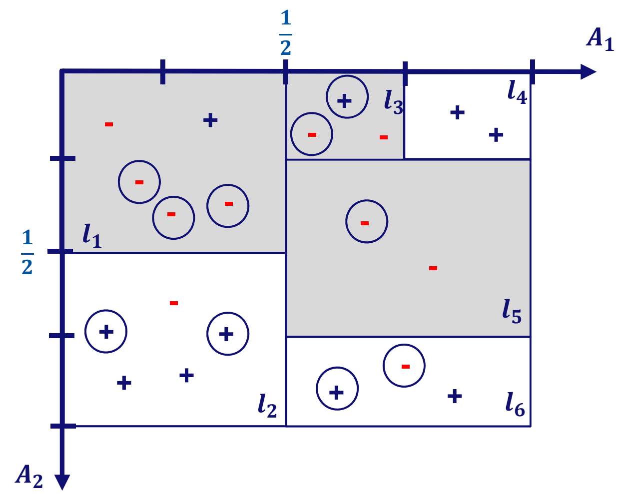
Discrimination (Solution)

If we want to relabel l_4, what would be the new label? and how this relabeling would affect the accuracy and discrimination?





Class	-	+	
$B = 1$	u	v	b
$B = 0$	w	x	$\bar{b}$
	n	p	a

Class	-	+	
$B = 1$	0	0	0
$B = 0$	0	2/20	2/20
	0	2/20	2/20

$$n < p$$

New label would be -

$$\Delta acc_l = n - p = -0.1$$

$$\Delta disc_l = \frac{u+v}{b} - \frac{w+x}{\bar{b}} = \frac{0}{\frac{1}{2}} - \frac{\frac{2}{20}}{\frac{1}{2}} = -0.2$$

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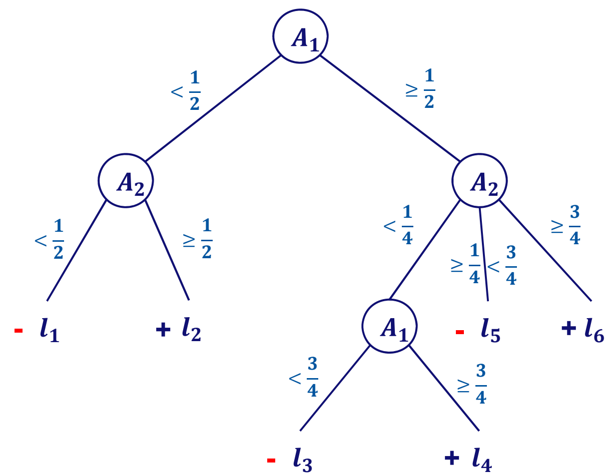
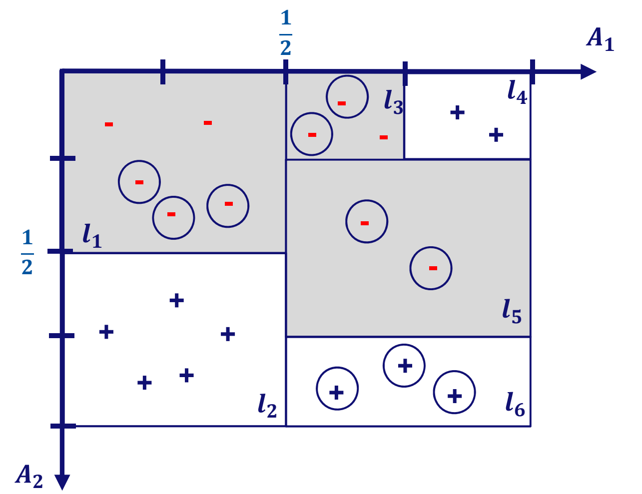
Discrimination (Your Turn)

In the following DT classifier, relabeling which leaf leads to the maximum reduction on the discrimination?





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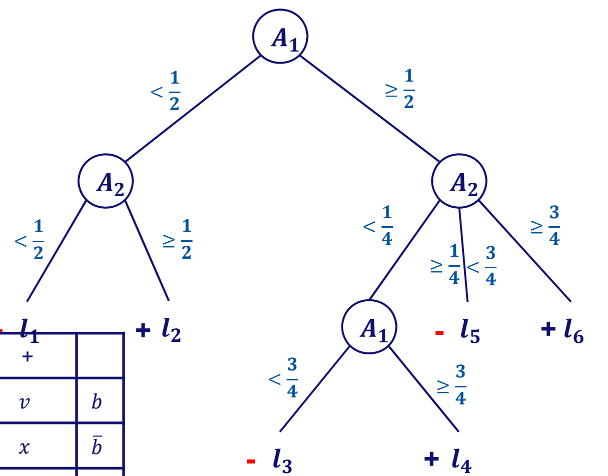
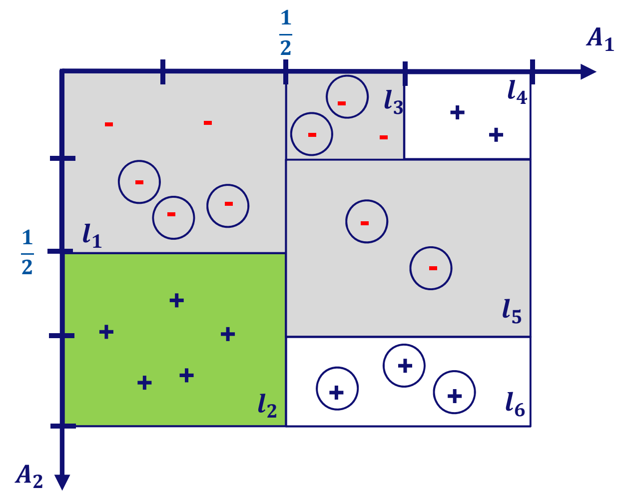
Discrimination (Solution)

In the following DT classifier, relabeling which leaf leads to the maximum reduction on the discrimination?





Class	-	+	
$B=1$	u	v	b
$B=0$	w	x	$\bar{b}$
	n	p	a

Class	-	+	
$B=1$	0	0	$\frac{4}{20}$
$B=0$	0	$\frac{4}{20}$	$\frac{2}{20}$
	$\frac{5}{20}$	$\frac{1}{20}$	$\frac{6}{20}$

$If\ p < n$

$$\Delta disc_l = \frac{0}{\frac{1}{2}} - \frac{\frac{4}{20}}{\frac{1}{2}} = -0.4$$

$If\ p > n$

$$\Delta disc_l = \frac{u+v}{b} - \frac{w+x}{\bar{b}}$$

1. The first step is to find the leaf with the maximum effect (positive or negative)

l_2 has the maximum effect on discrimination. Because it leads to maximum difference between examples with discriminatory and non-discriminatory attribute.

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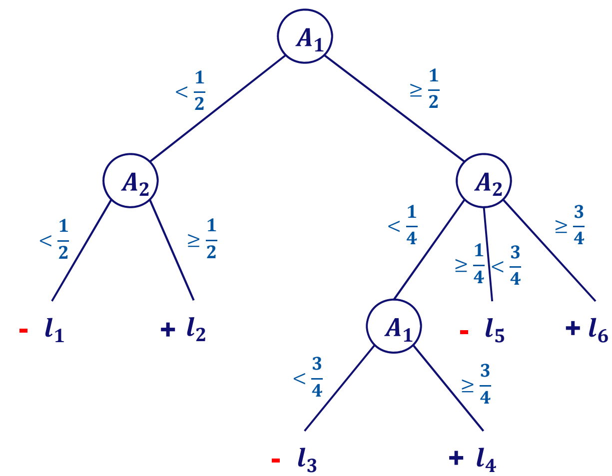
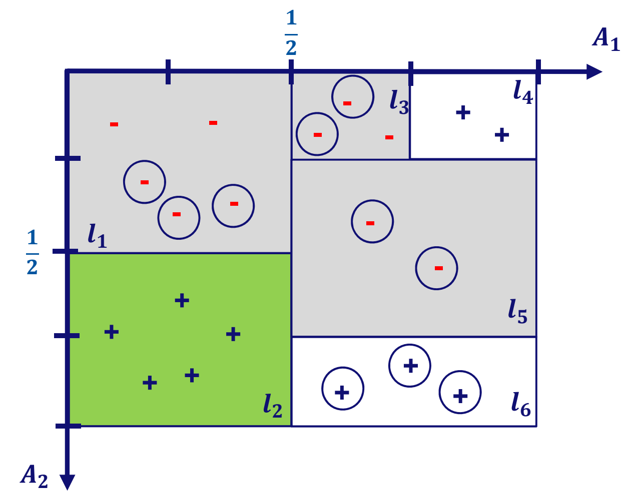
Discrimination (Solution)

In the following DT classifier, relabeling which leaf leads to the maximum reduction on the discrimination?





Probability of getting a positive label for an instance with B = 0

$$disc_T = \frac{W_2 + X_2}{\bar{b}} - \frac{U_2 + V_2}{b}$$

Probability of getting a positive label for an instance with B = 0

2. The aim is to either decrease the first part or increase the second part in the discrimination formula.

Relabeling l_2 leads to maximum reduction (0.5) of the first part and consequently causes maximum reduction of discrimination.

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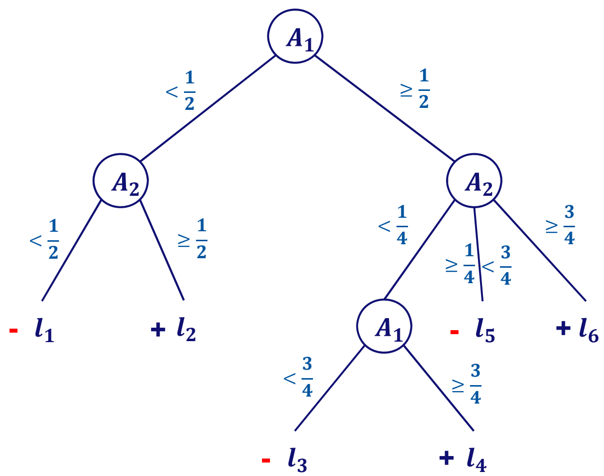
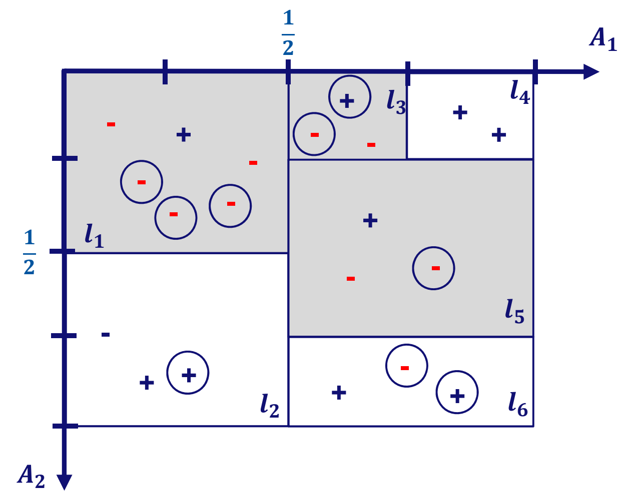
Discrimination (Your Turn)

In the following DT classifier, relabeling which leaf has the maximum effect on the accuracy?





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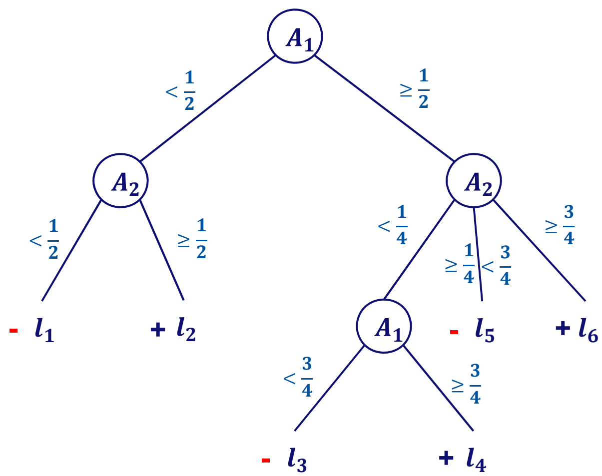
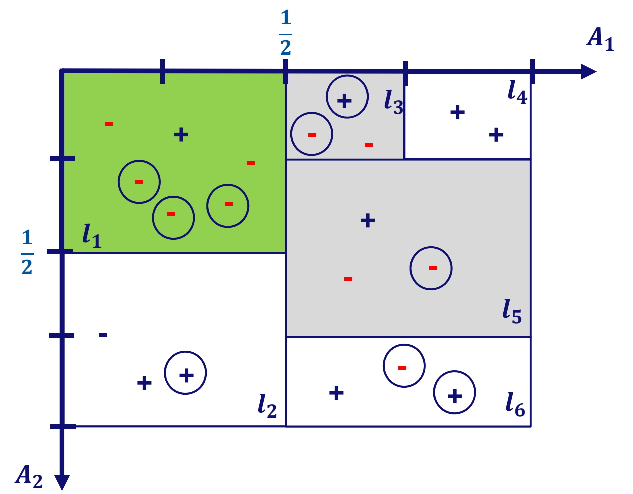
Discrimination (Solution)

In the following DT classifier, relabeling which leaf has the maximum effect on the accuracy?





Of course l_1 contains the examples which lead to maximum difference between labels ($\frac{1}{20} - \frac{5}{20} = -\frac{4}{20}$). Therefore, relabeling this leaf has the maximum effect on the accuracy.

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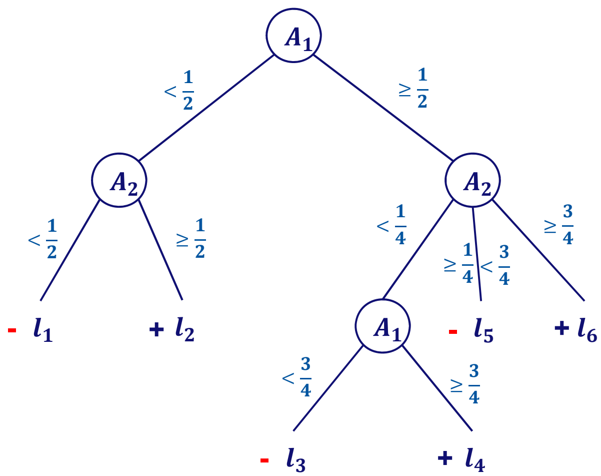
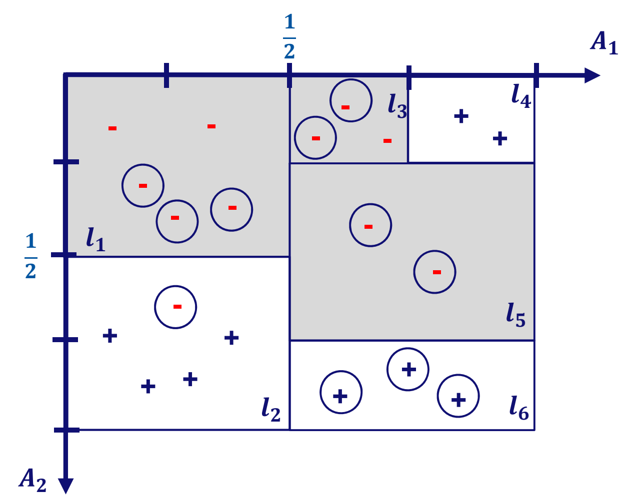
Discrimination (Homework)

In the following DT classifier, relabeling which leaf leads to the maximum reduction of the discrimination, and minimum reduction of the accuracy (the best leaf for relabeling)?





Discrimination (Homework)

What is the first node of the decision tree for the following table of data with respect to accuracy and fairness? (use $IGC - IGS$)

Sex	Exp	Degree	Job	Class
F	Exp >10	HS	Board	-
M	5< Exp <10	Uni	Board	+
M	Exp >10	HS	Board	-
M	5< Exp <10	HS	Hcare	+
M	Exp < 5	HS	Hcare	+
F	Exp < 5	HS	Board	-
M	Exp < 5	None	Edu	-
F	Exp >10	None	Hcare	-
M	Exp < 5	Uni	Edu	+
M	Exp >10	Uni	Board	+

$$IGC := H_{Class}(D) - \sum_{i=1}^{k} \frac{|D_i|}{|D|} H_{Class}(D_i)$$

$$IGS := H_B(D) - \sum_{i=1}^{k} \frac{|D_i|}{|D|} H_B(D_i)$$

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Confidentiality

Suppose that we have such a following tables of information about people and what they bought from an online grocery shop.

Name	Age	Gender	State of domicile	Religion	Product
Ramsha	22	Female	Tamil Nadu	Hindu	Pea
Yadu	24	Female	Kerala	Hindu	Bean
Salima	25	Female	Tamil Nadu	Muslim	Peanut
Sunny	25	Male	Karnataka	Buddhist	Pea
Joan	24	Female	Kerala	Muslim	Bean
Bahuksana	23	Male	Karnataka	Buddhist	Lentil
Rambha	19	Male	Kerala	Christian	Peanut
Kishor	24	Male	Karnataka	Buddhist	Lentil
Johnson	17	Male	Kerala	Christian	Peanut
John	19	Male	Kerala	Christian	Pea

Specify type of each attribute:

- **Explicit Identifier**
- **Quasi-identifier**
- **Sensitive**

Convert this data to 2-anonymity table.

Confidentiality

Explicit identifier

Quasi-identifiers

Sensitive

Name	Age	Gender	State of domicile	Religion	Product
Ramsha	22	Female	Tamil Nadu	Hindu	Pea
Yadu	24	Female	Kerala	Hindu	Bean
Salima	25	Female	Tamil Nadu	Muslim	Peanut
Sunny	25	Male	Karnataka	Buddhist	Pea
Joan	24	Female	Kerala	Muslim	Bean
Bahuksana	23	Male	Karnataka	Buddhist	Lentil
Rambha	19	Male	Kerala	Christian	Peanut
Kishor	24	Male	Karnataka	Buddhist	Lentil
Johnson	17	Male	Kerala	Christian	Peanut
John	19	Male	Kerala	Christian	Pea

Confidentiality

2-anonymity

- **Data is k-anonymity if each equivalence class contains at least k records.**
- **Equivalence class is a set of records that have the same values for the quasi-identifiers.**

Name	Age	Gender	State of domicile	Religion	Product
*	20 < Age ≤ 25	Female	Tamil Nadu	*	Pea
*	20 < Age ≤ 25	Female	Kerala	*	Bean
*	20 < Age ≤ 25	Female	Tamil Nadu	*	Peanut
*	20 < Age ≤ 25	Male	Karnataka	*	Pea
*	20 < Age ≤ 25	Female	Kerala	*	Bean
*	20 < Age ≤ 25	Male	Karnataka	*	Lentil
*	Age ≤ 20	Male	Kerala	*	Peanut
*	20 < Age ≤ 25	Male	Karnataka	*	Lentil
*	Age ≤ 20	Male	Kerala	*	Peanut
*	Age ≤ 20	Male	Kerala	*	Pea

2-anonymity, distinct 2-diversity

- **Data is distinct l-diversity if there are at least l distinct values for the sensitive attribute in each equivalence class.**

Name	Age	Gender	State of domicile	Religion	Product
*	20 < Age ≤ 25	Female	*	Hindu	Pea
*	20 < Age ≤ 25	Female	*	Hindu	Bean
*	20 < Age ≤ 25	Female	*	Muslim	Peanut
*	20 < Age ≤ 25	Male	*	Buddhist	Pea
*	20 < Age ≤ 25	Female	*	Muslim	Bean
*	20 < Age ≤ 25	Male	*	Buddhist	Lentil
*	Age ≤ 20	Male	*	Christian	Peanut
*	20 < Age ≤ 25	Male	*	Buddhist	Lentil
*	Age ≤ 20	Male	*	Christian	Peanut
*	Age ≤ 20	Male	*	Christian	Pea

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Confidentiality

- **Entropy l-diversity.**
  - **The entropy of an equivalence class E is defined to be**
    - $Entropy(E) = -\sum_{s \in S} p(E,s) log(p(E,s))$
    - **In which S is the domain of the sensitive attribute, and $p(E,s)$ is the fraction of records in E that have sensitive value s.**
  - **A table is said to have entropy l-diversity if for every equivalence class E, $Entropy(E) \geq log(l)$.**

Confidentiality (Your Turn)

What is the maximum value for l based on the following table which has 2-anonimity and entropy l-diversity?

Name	Age	Gender	State of domicile	Religion	Product
*	20 < Age ≤ 25	Female	*	Hindu	Pea
*	20 < Age ≤ 25	Female	*	Hindu	Bean
*	20 < Age ≤ 25	Female	*	Muslim	Peanut
*	20 < Age ≤ 25	Male	*	Buddhist	Pea
*	20 < Age ≤ 25	Female	*	Muslim	Bean
*	20 < Age ≤ 25	Male	*	Buddhist	Lentil
*	Age ≤ 20	Male	*	Christian	Peanut
*	20 < Age ≤ 25	Male	*	Buddhist	Lentil
*	Age ≤ 20	Male	*	Christian	Peanut
*	Age ≤ 20	Male	*	Christian	Pea

Confidentiality (Solution)

What is the maximum value for l to have based on the following table which has entropy l-diversity?

Name	Age	Gender	State of domicile	Religion	Product
*	20 < Age ≤ 25	Female	*	Hindu	Pea
*	20 < Age ≤ 25	Female	*	Hindu	Bean
*	20 < Age ≤ 25	Female	*	Muslim	Peanut
*	20 < Age ≤ 25	Male	*	Buddhist	Pea
*	20 < Age ≤ 25	Female	*	Muslim	Bean
*	20 < Age ≤ 25	Male	*	Buddhist	Lentil
*	Age ≤ 20	Male	*	Christian	Peanut
*	20 < Age ≤ 25	Male	*	Buddhist	Lentil
*	Age ≤ 20	Male	*	Christian	Peanut
*	Age ≤ 20	Male	*	Christian	Pea

Entropy = 1

Entropy = 1

Entropy = 0.92

Entropy = 0.92

$$\boldsymbol{Entropy(E) \geq log(l)} \qquad \boldsymbol{log(l) = 0.92} \qquad \boldsymbol{l = 1.9}$$

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Confidentiality

- Recursive (c,l)-diversity.
  - Let m be the number of values in an equivalence class, and $r_i, 1 \leq i \leq m$ be the number of times that the i th most frequent sensitive value appears in an equivalence class E (they are sorted in descending order).
  - Then E is said to have recursive (c,l)-diversity if $r_1 < c(r_l + r_{l+1} + \cdots + r_m)$. Where c is a constant.
    - We say that an equivalence class is (c,2)-diverse if $r_1 < c(r_2 + \cdots + r_m)$ for some user-specific constant c.
    - For l > 2, we say that an equivalence class satisfies recursive (c,l)-diversity if we can eliminate one sensitive value in the equivalence class and still have (c,l-1)-diversity.
  - A table is said to have recursive (c,l)-diversity if all of its equivalence classes have recursive (c,l)-diversity.

Confidentiality (Your Turn)

- **Assume the following list as the list of frequency of sensitive values in an equivalence class.**
  - **Does the corresponding equivalence class have recursive (1,2)-diversity?**
  - **Does the corresponding equivalence class have recursive (2,3)-diversity?**

- $Frequency\ list\ = (\boldsymbol{r_1} = \mathbf{500}, \boldsymbol{r_2} = \mathbf{400}, \boldsymbol{r_3} = \mathbf{200}, \boldsymbol{r_4} = \mathbf{50}, \boldsymbol{r_5} = \mathbf{20})$

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Confidentiality (Solution)

- **Assume the following list as the list of frequency of sensitive values in an equivalence class.**
  - **Does the corresponding equivalence class have recursive (1,2)-diversity?**
  - **Does the corresponding equivalence class have recursive (2,3)-diversity?**

- $\mathit{Frequency\ list} = (\boldsymbol{r_1 = 500, r_2 = 400, r_3 = 200, r_4 = 50, r_5 = 20})$

$$\boldsymbol{r_1 < c(r_l + r_{l+1} + \cdots + r_m)}$$

$\boldsymbol{r_1 < 1(r_2 + r_3 + r_4 + r_5)}$ $\boldsymbol{l = 2, c = 1}$

$\boldsymbol{500 < 1(400 + 200 + 50 + 20)}$ **The corresponding equivalence class has recursive (1,2)-diversity**

$\boldsymbol{r_1 < 2(r_3 + r_4 + r_5)}$ $\boldsymbol{l = 3, c = 2}$

$\boldsymbol{500 < 2(200 + 50 + 20)}$ **The corresponding equivalence class has recursive (2,3)-diversity**