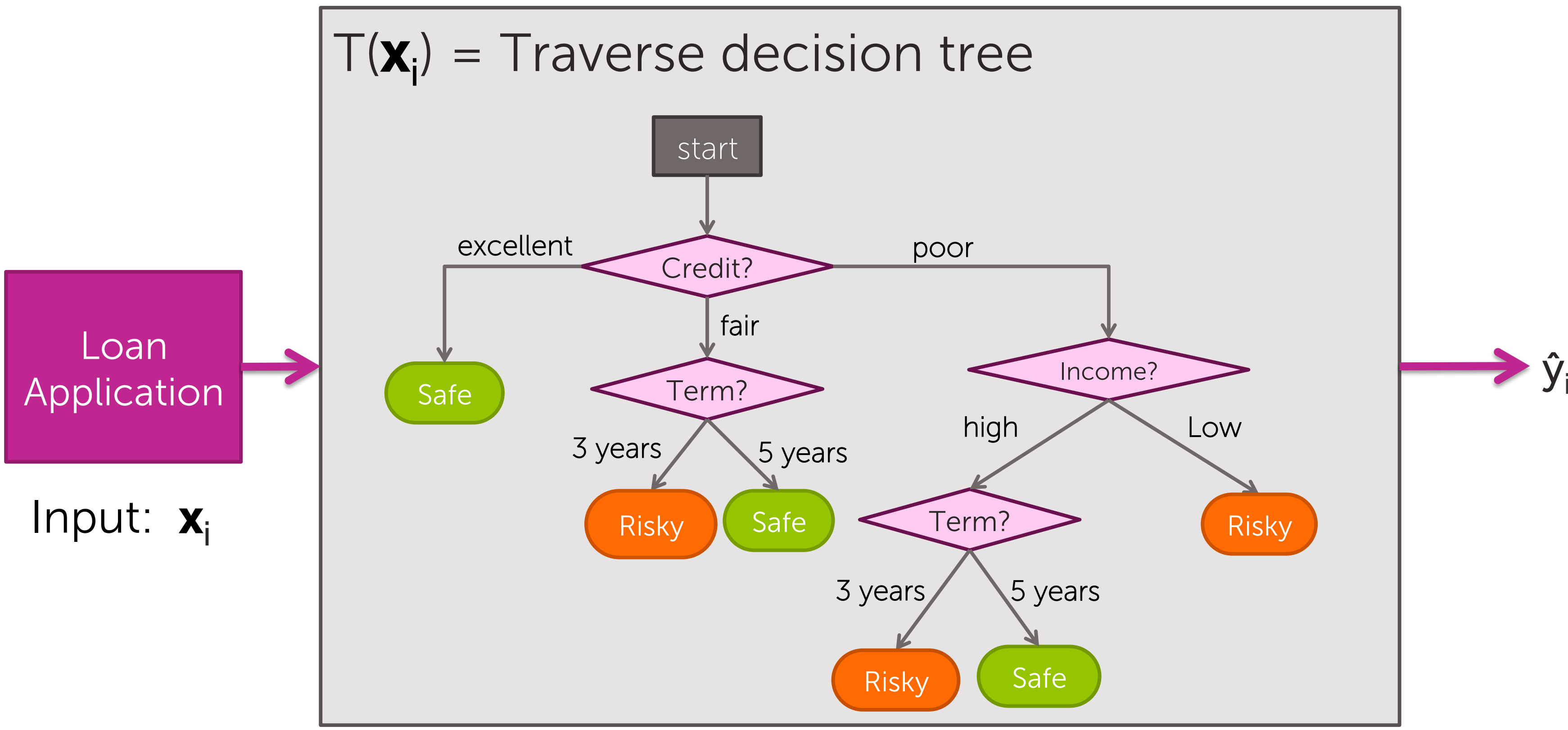
Handling missing data

Emily Fox & Carlos Guestrin
Machine Learning Specialization
University of Washington

Decision tree review



So far: data always completely observed

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	5 yrs	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	low	safe
poor	3 yrs	high	risky
poor	5 yrs	low	safe
fair	3 yrs	high	safe

Known **x** and y values for all data points

Missing data

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	?	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	?	high	risky
poor	5 yrs	low	safe
fair	?	high	safe

Loan application
may be
3 or 5 years

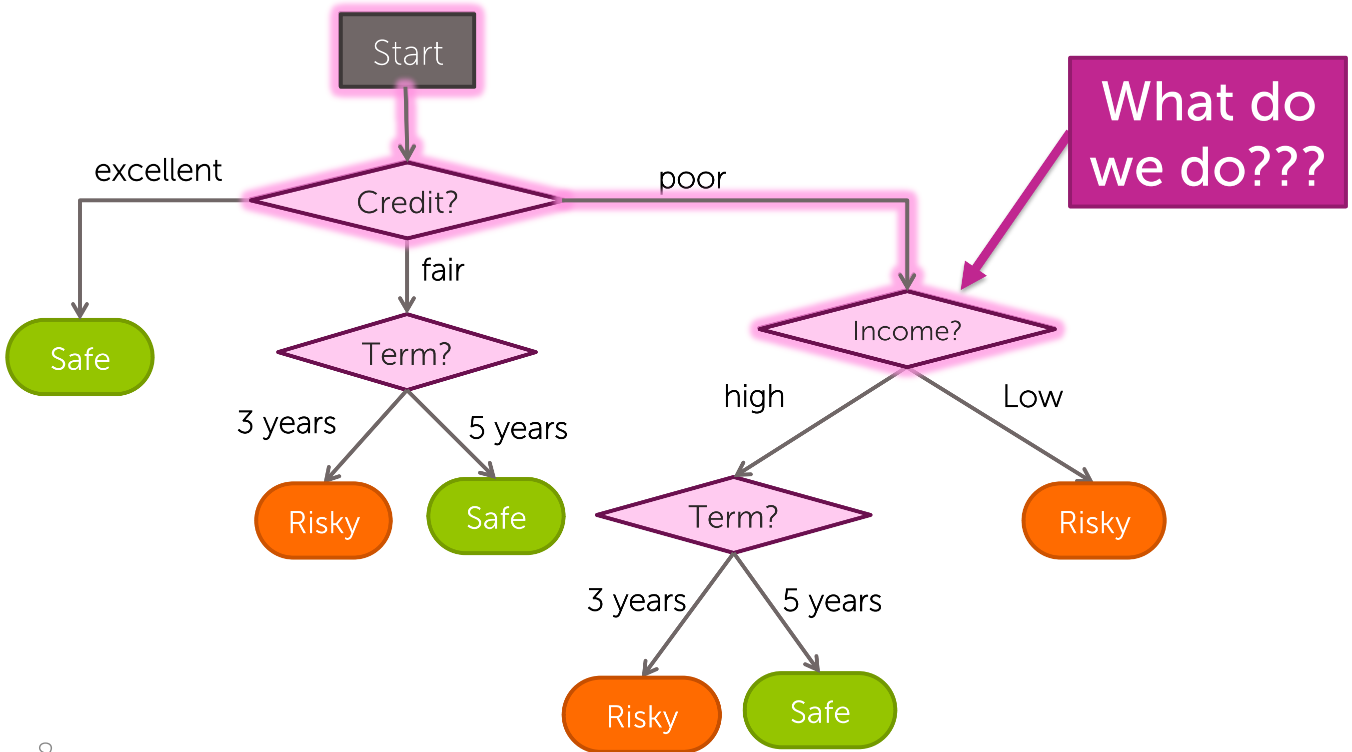
Missing values impact training and predictions

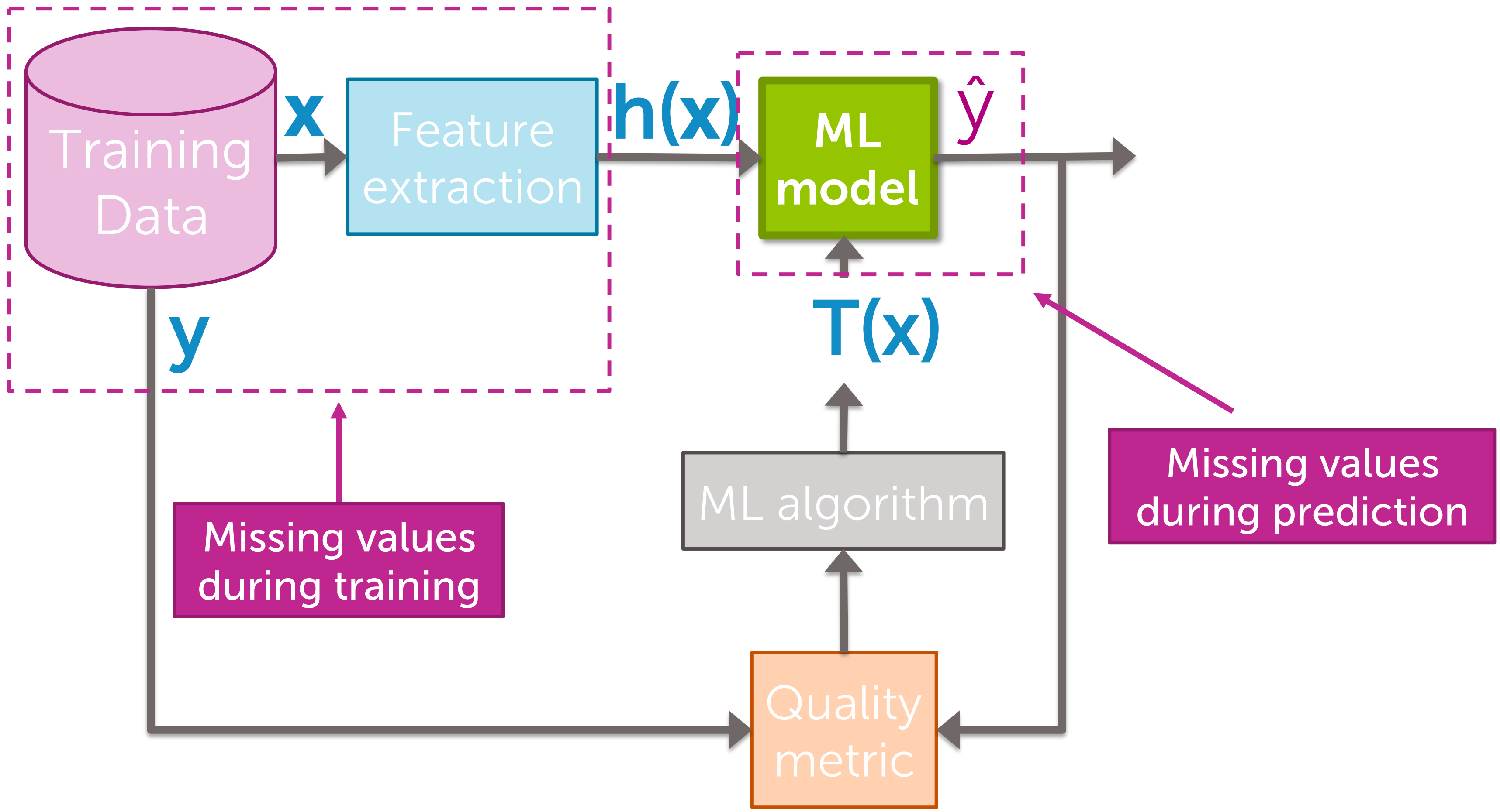
1. **Training data:** Contains "unknown" values

2. **Predictions:** Input at prediction time contains "unknown" values

Missing values during prediction

$\mathbf{x}_i$ = (Credit = poor, Income = ?, Term = 5 years)

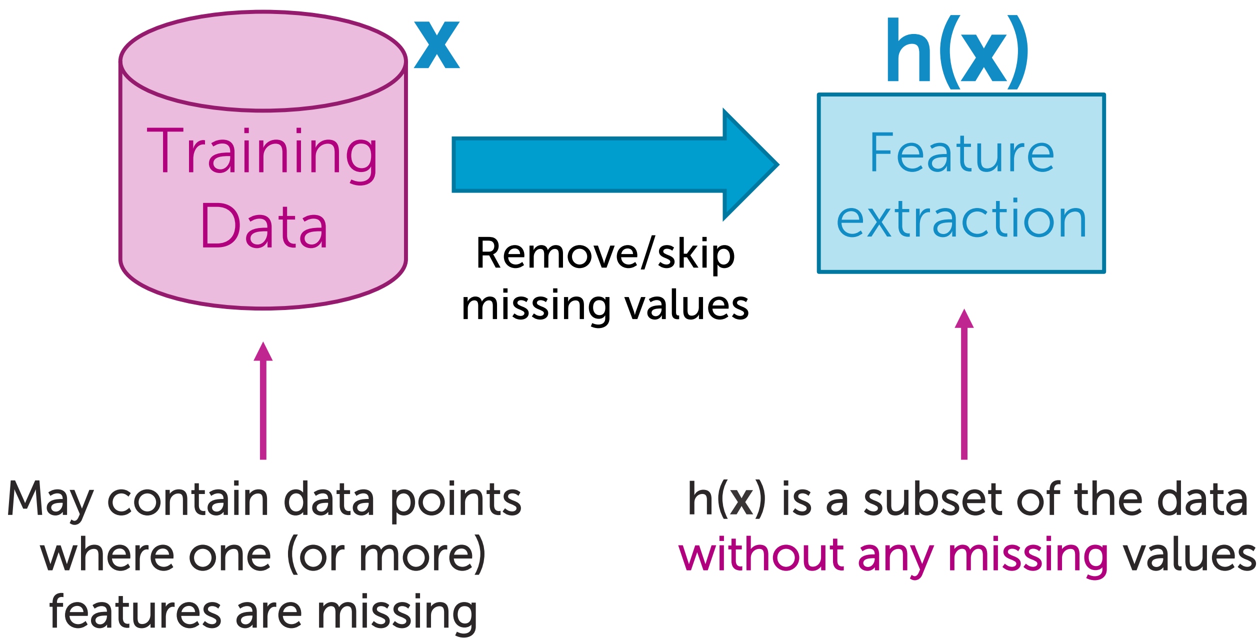



Training Data
x
Feature extraction
h(x)
ML model
ŷ
y
T(x)
ML algorithm
Quality metric
Missing values during training
Missing values during prediction

Handling missing data

***Strategy 1**: Purification by skipping*

Idea 1: Purification by skipping/removing



Idea 1: Skip data points with missing values

x

N = 9, 3 features

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	?	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	low	risky
poor	3 yrs	?	safe
fair	?	high	safe

fewer

Skip data points with missing values

h(x)

N = 6, 3 features

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	low	risky

The challenge with Idea 1

x

N = 9, 3 features

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	?	low	risky
fair	3 yrs	high	safe
poor	?	high	risky
excellent	?	low	risky
fair	?	high	safe
poor	3 yrs	low	risky
poor	?	low	safe
fair	?	high	safe

Warning: More than 50% of the loan terms are unknown!

much much smaller

Skip data points with missing values

h(x)

N = 3, 3 features

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	3 yrs	high	safe
poor	3 yrs	low	risky

Idea 2: Skip features with missing values

x

fewer features

h(x)

N = 9, 3 features

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	?	low	risky
fair	3 yrs	high	safe
poor	?	high	risky
excellent	?	low	risky
fair	5 yrs	high	safe
poor	?	high	risky
poor	?	low	safe
fair	?	high	safe

Skip features with many missing values

N = 9, 2 features

Credit	Income	y
excellent	high	safe
fair	low	risky
fair	high	safe
poor	high	risky
excellent	low	risky
fair	high	safe
poor	high	risky
poor	low	safe
fair	high	safe

Missing value skipping: Ideas 1 & 2

Idea 1: Skip data points where any feature contains a missing value

- Make sure only a few data points are skipped

Idea 2: Skip an entire feature if it's missing for many data points

- Make sure only a few features are skipped

Missing value skipping: Pros and Cons

Pros

- Easy to understand and implement
- Can be applied to any model (decision trees, logistic regression, linear regression,…)

Cons

- Removing data points and features may remove important information from data
- Unclear when it's better to remove data points versus features
- Doesn't help if data is missing at prediction time

Handling missing data

Strategy 2: Prification by imputing

Main drawback of skipping strategy

x

N = 9, 3 features

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	?	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	low	risky
poor	?	low	safe
fair	?	high	safe

Data is precious, don't throw it away!

Skip data points with missing values

h(x)

N = 6, 3 features

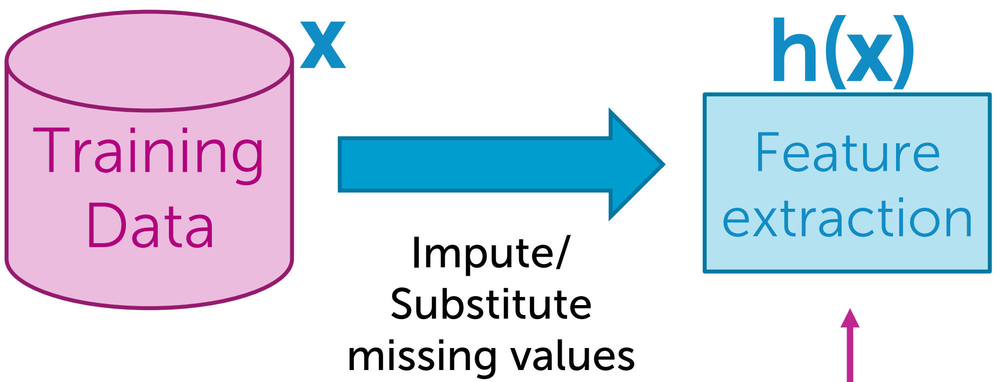
Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	low	risky

Can we keep all the data?

credit	term	income	y
excellent	3 yrs	high	safe
fair	?	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	high	risky
poor	?	low	safe
fair	?	high	safe

Use other data points in **x** to "guess" the "?"

Idea 2: Purification by imputing



Same number of data points as the original data

Idea 2: Imputation/Substitution

N = 9, 3 features

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	?	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	high	risky
poor	?	low	safe
fair	?	high	safe

Fill in each missing value with a calculated guess

N = 9, 3 features

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	**3 yrs**	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	high	risky
poor	**3 yrs**	low	safe
fair	**3 yrs**	high	safe

Example: Replace ? with most common value

simple

# 3 year loans: 4	← Best guess
# 5 year loans: 2	

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	?	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	high	risky
poor	?	low	safe
fair	?	high	safe

Purification by imputing →

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	**3 yrs**	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	high	risky
poor	**3 yrs**	low	safe
fair	**3 yrs**	high	safe

Common (simple) rules for purification by imputation

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	?	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	high	safe
poor	3 yrs	high	risky
poor	?	low	safe
fair	?	high	safe

Impute each feature with missing values:

1. **Categorical features use mode**: Most popular value (mode) of non-missing $\mathbf{x}_i$
2. **Numerical features use average or median**: Average or median value of non-missing $\mathbf{x}_i$

Many advanced methods exist, e.g., expectation-maximization (EM) algorithm

Missing value imputation: Pros and Cons

Pros

- Easy to understand and implement
- Can be applied to any model
  (decision trees, logistic regression, linear regression,…)
- Can be used at prediction time: use same imputation rules

Cons

- May result in systematic errors

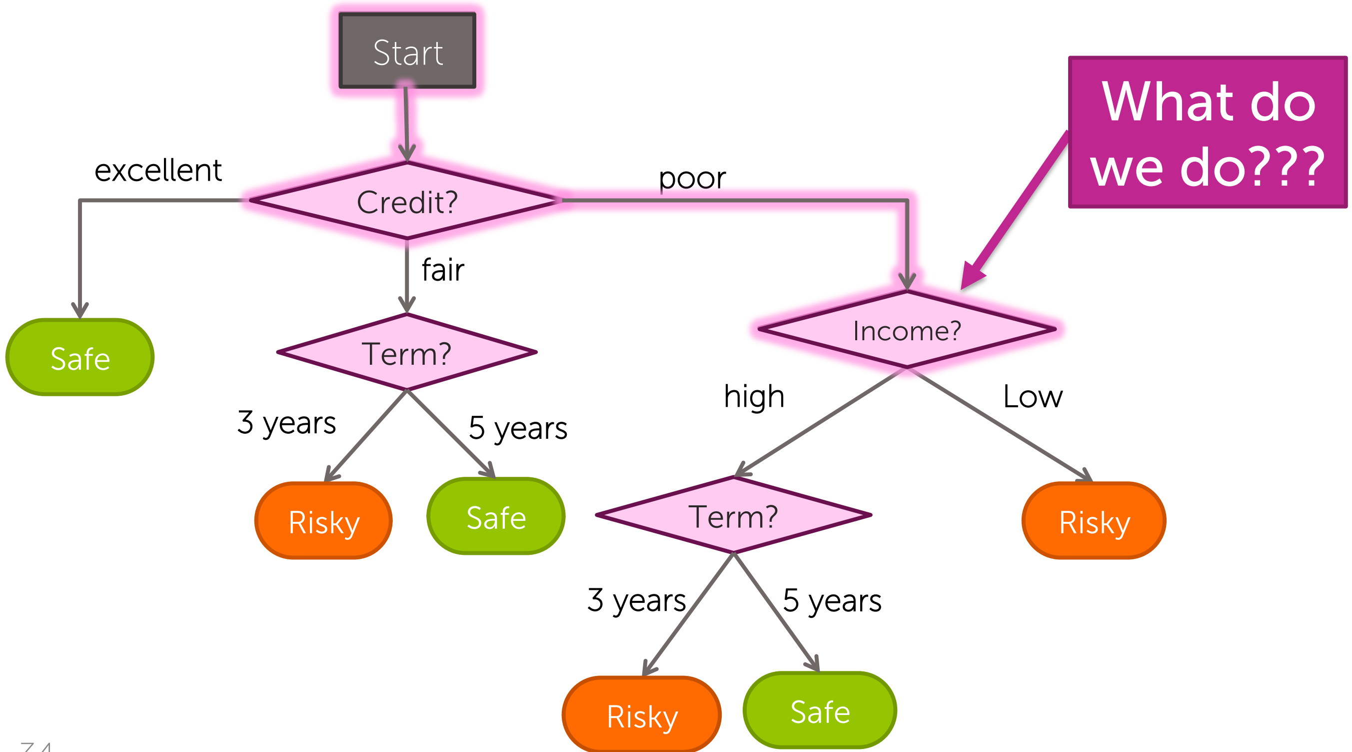
Example: Feature “age” missing in all banks in Washington by state law

Handling missing data

***Strategy 3**: Adapt learning algorithm to be robust to missing values*

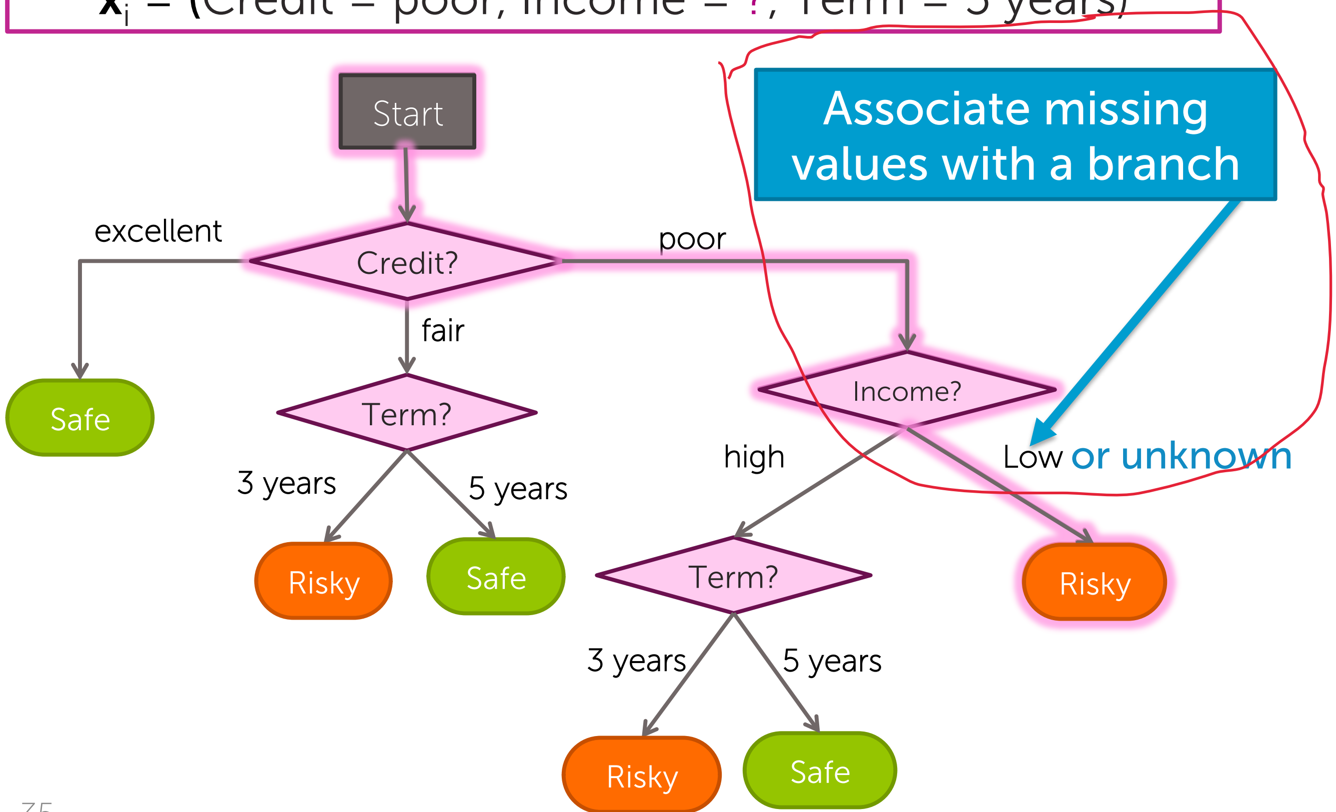
Missing values during prediction: *revisited*

$\mathbf{x}_i$ = (Credit = poor, Income = ?, Term = 5 years)

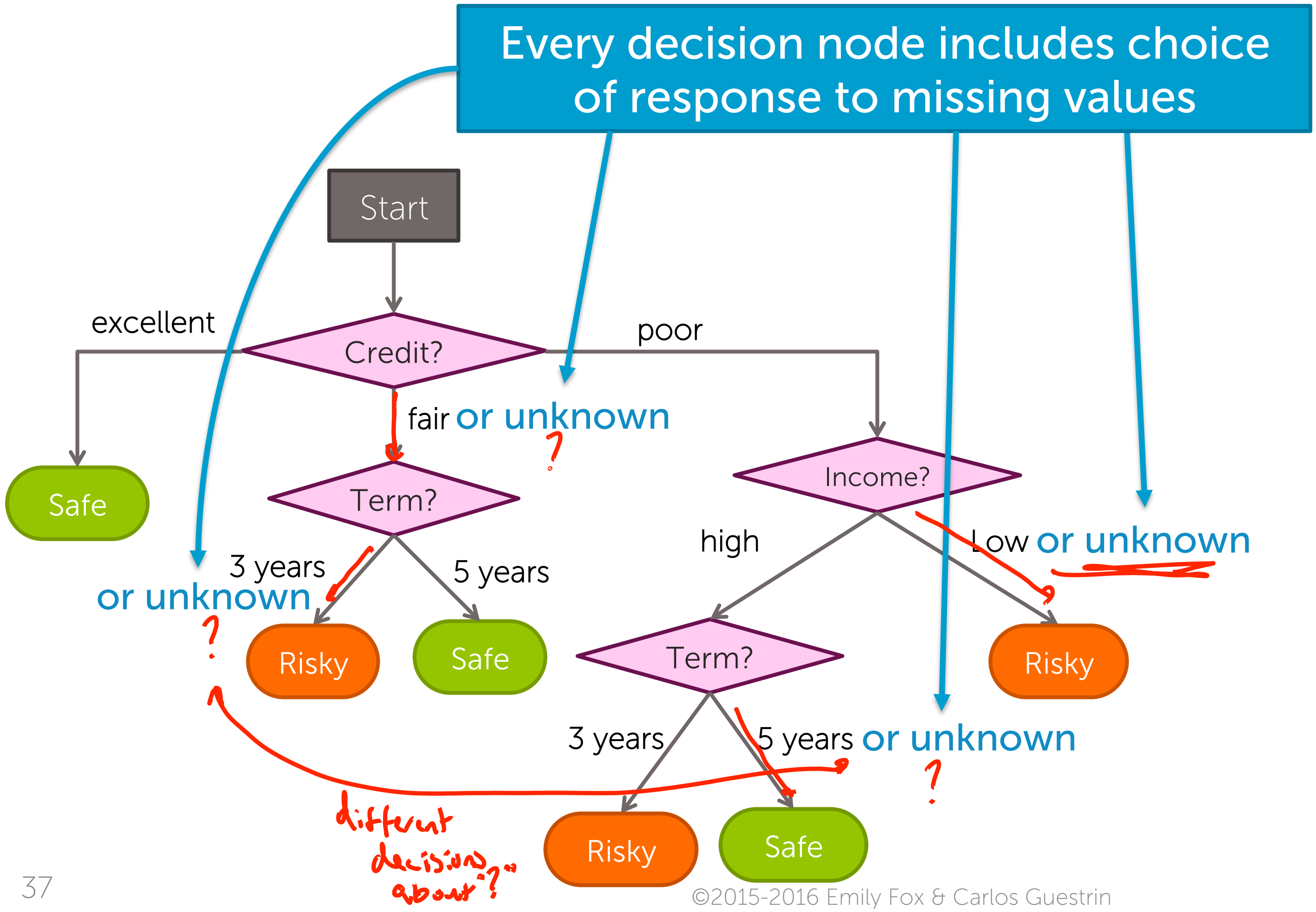


Add missing values to the tree definition

$\mathbf{x}_i$ = (Credit = poor, Income = ?, Term = 5 years)

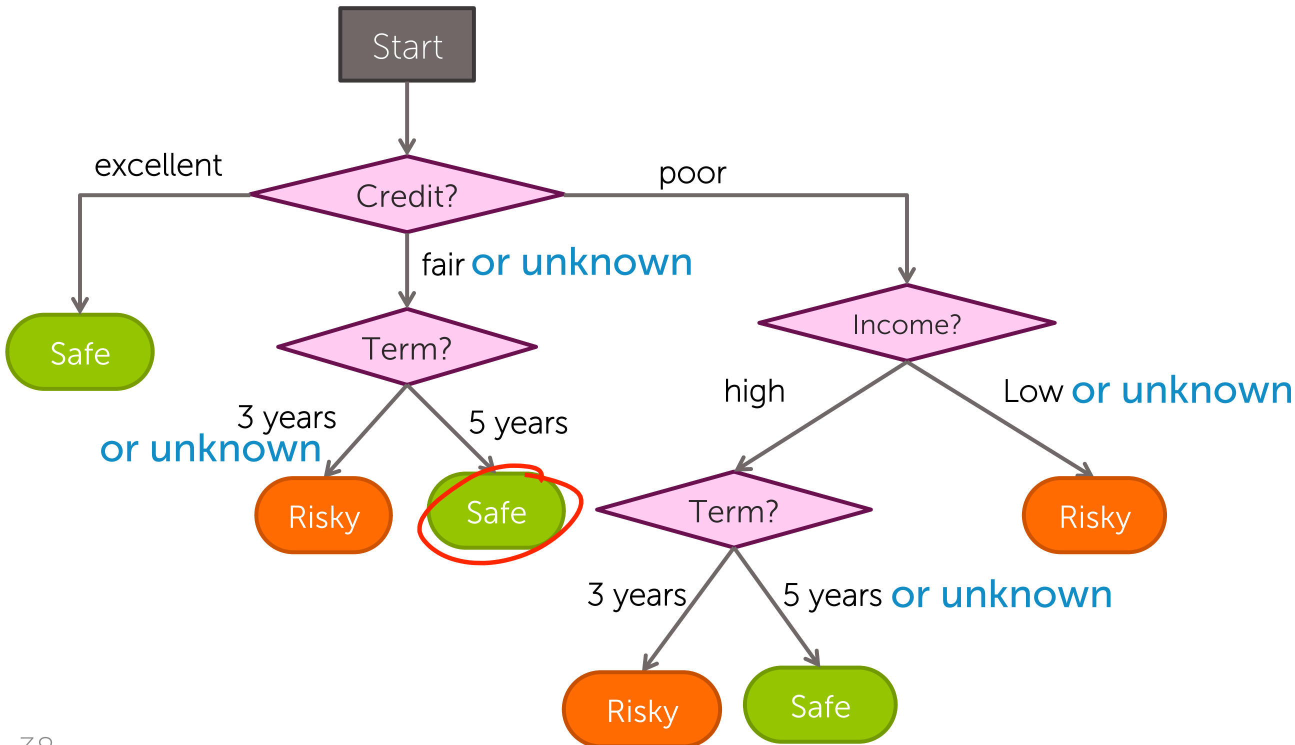


Add missing value choice to every decision node



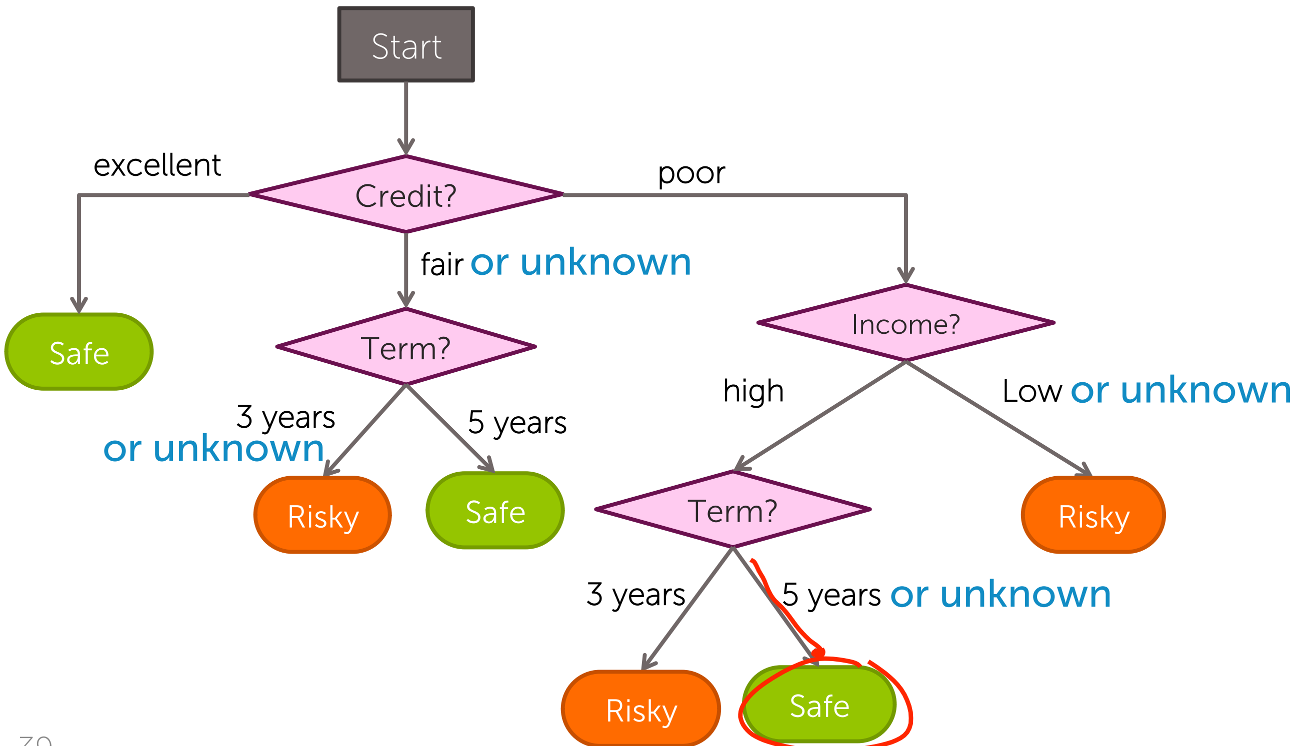
Prediction with missing values becomes simple

$\mathbf{x}_i$ = (Credit = ?, Income = high, Term = 5 years)



Prediction with missing values becomes simple

$\mathbf{x}_i$ = (Credit = poor, Income = high, Term = ?)



Explicitly handling missing data by learning algorithm: Pros and Cons

Pros
- Addresses training and prediction time
- **More accurate predictions**

Cons
- Requires modification of learning algorithm
  - Very simple for decision trees

Feature split selection with missing data

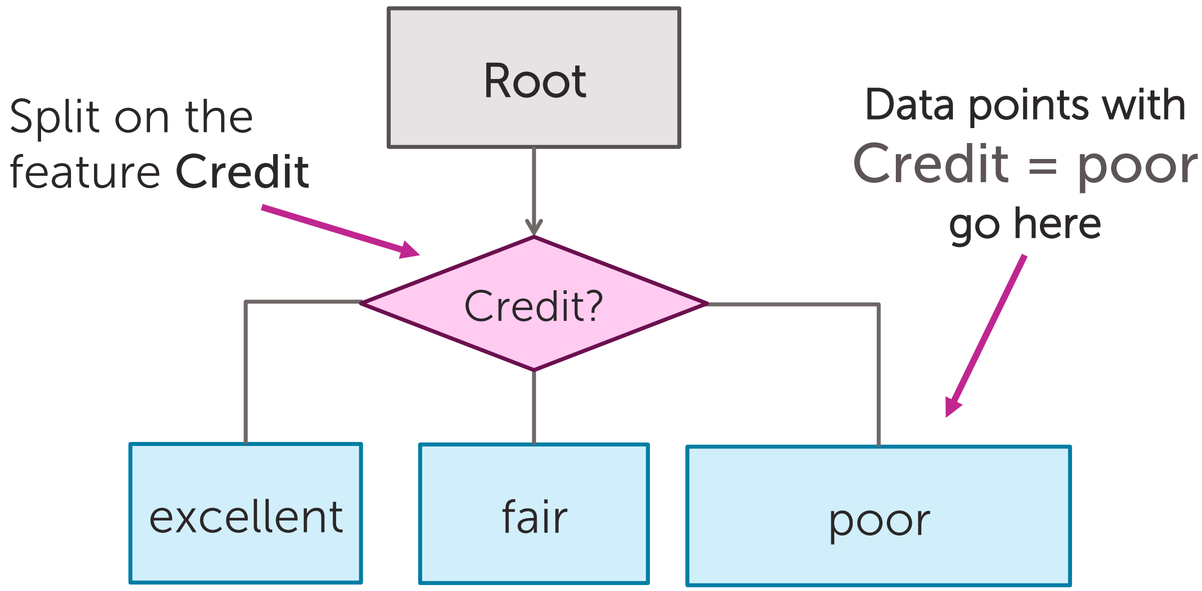
Greedy decision tree learning

- Step 1: Start with an empty tree
- Step 2: Select a feature to split data
- For each split of the tree:
  - Step 3: If nothing more to, make predictions
  - Step 4: Otherwise, go to Step 2 & continue (recurse) on this split

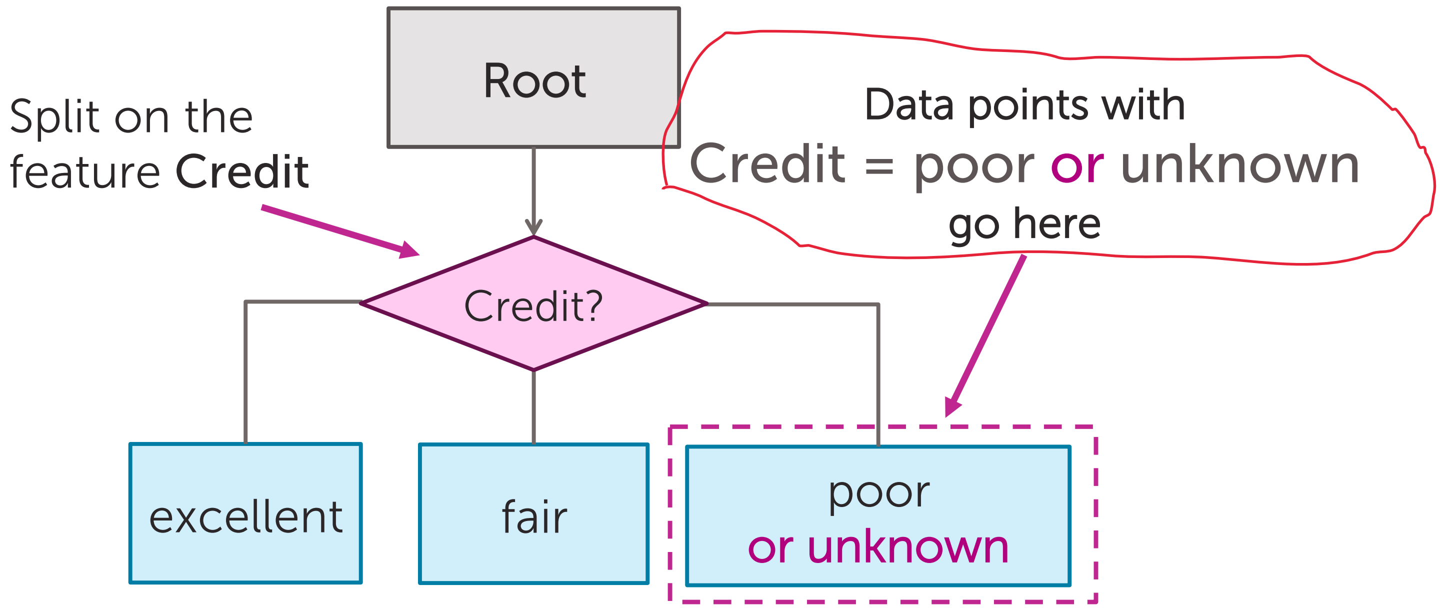
Pick feature split leading to lowest classification error

Must select feature & branch for missing values!

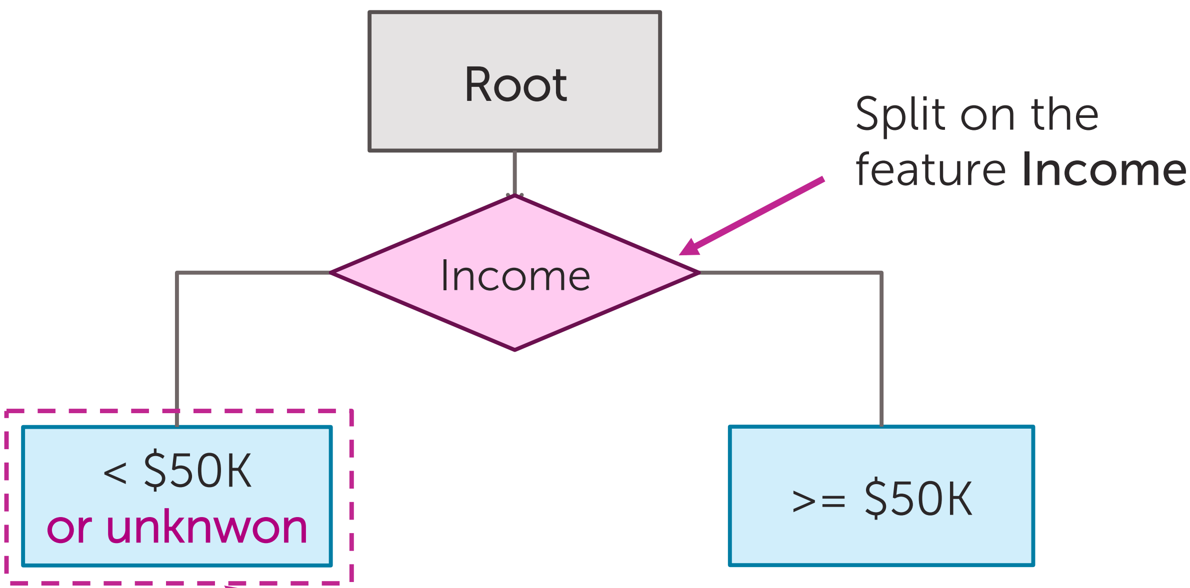
Feature split (without missing values)



Feature split (with missing values)



Missing value handling in threshold splits



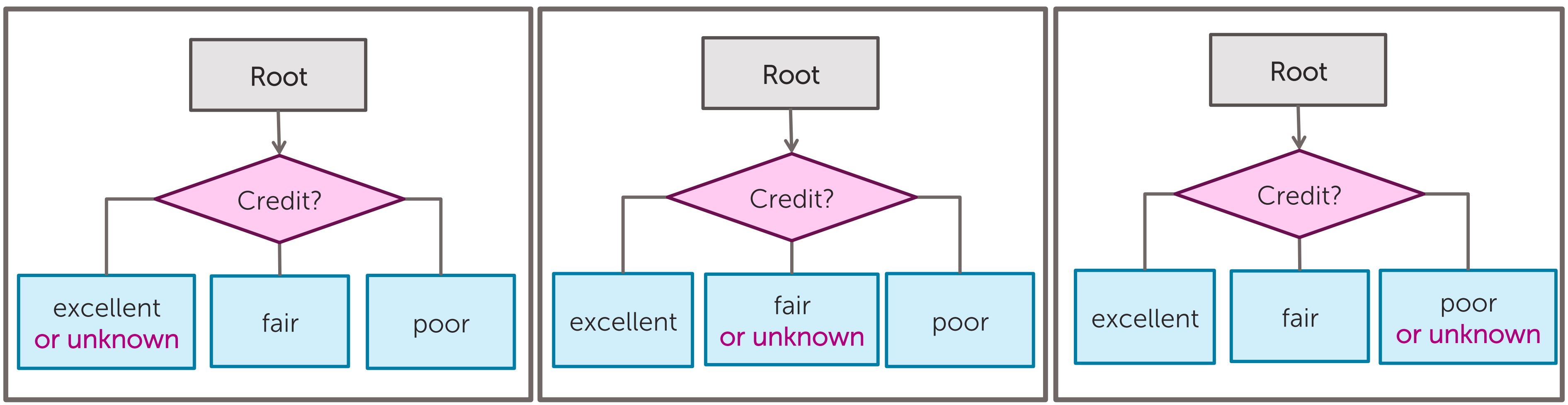
Should missing go left, right, or middle?

Choose branch that leads to lowest classification error!

Choice 1: Missing values go with Credit=excellent

Choice 2: Missing values go with Credit=fair

Choice 3: Missing values go with Credit=poor



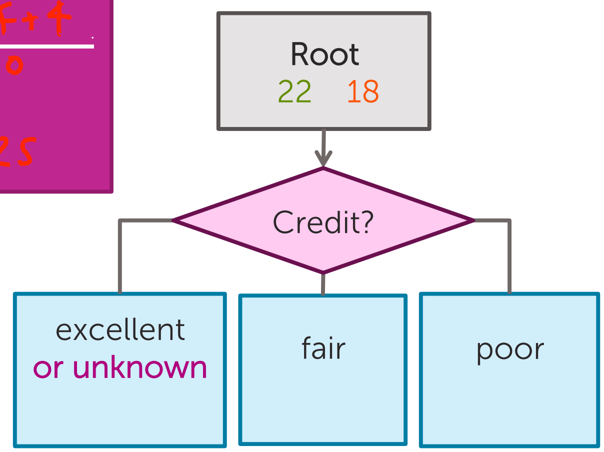
Computing classification error of decision stump with missing data

N = 40, 3 features

Credit	Term	Income	y
excellent	3 yrs	high	safe
?	5 yrs	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
?	3 yrs	low	risky
?	5 yrs	low	safe
poor	3 yrs	high	risky
poor	5 yrs	low	safe
fair	3 yrs	high	safe
…	…	…	…

$$\text{Error} = \frac{2+4+4}{40}$$

$$= 0.25$$

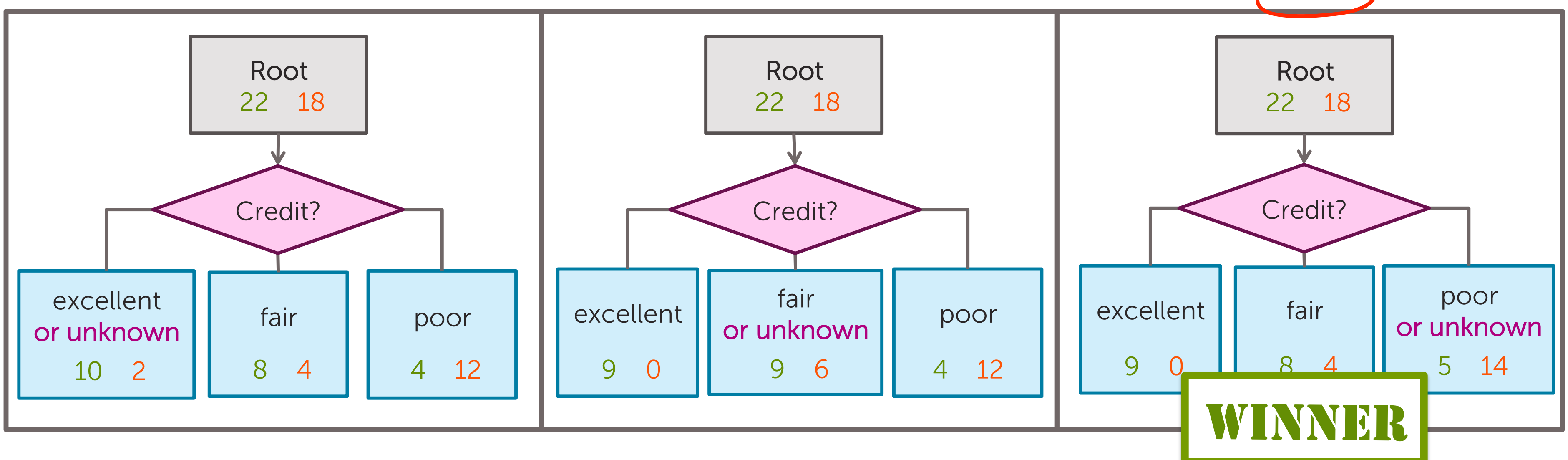


Observed values	9 0	8 4	4 12

Use classification error to decide

Best choice → assign "unknown" to Credit = poor

Choice 1: error = 0.25 Choice 2: error = 0.25 Choice 3: error = 0.225



Feature split selection algorithm with missing value handling

- Given a subset of data M (a node in a tree)
- For each feature $h_i(x)$:
  1. Split data points of M where $h_i(x)$ is *not* "unknown" according to feature $h_i(x)$
  2. Consider assigning data points with "unknown" value for $h_i(x)$ to each branch
     A. Compute classification error split & branch assignment of "unknown" values
- Chose feature $h^*(x)$ & branch assignment of "unknown" with lowest classification error

Summary of handling missing data

What you can do now…

Describe common ways to handling missing data:

1. Skip all rows with any missing values
2. Skip features with many missing values
3. Impute missing values using other data points

Modify learning algorithm (decision trees) to handle missing data:

1. Missing values get added to one branch of split
2. Use classification error to determine where missing values go

Thank you to Dr. Krishna Sridhar

Dr. Krishna Sridhar

Staff Data Scientist, Dato, Inc.