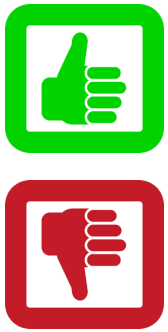


Decision Trees, Bagging and Boosting

CSE 446: Machine Learning

created by Emily Fox

Predicting potential loan defaults

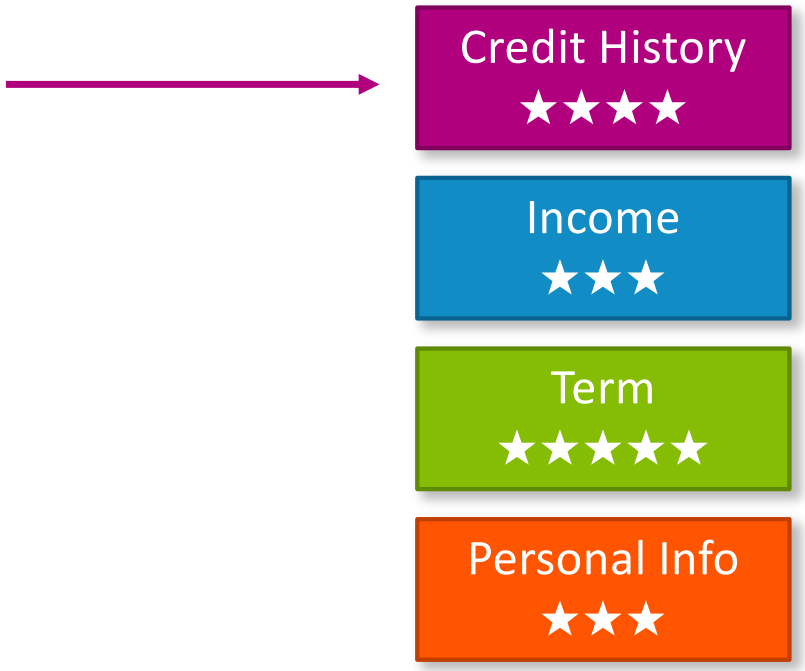
What makes a loan risky?

- Credit History ★★★★
- Income ★★★
- Term ★★★★★
- Personal Info ★★★

Credit history explained

Did I pay previous loans on time?

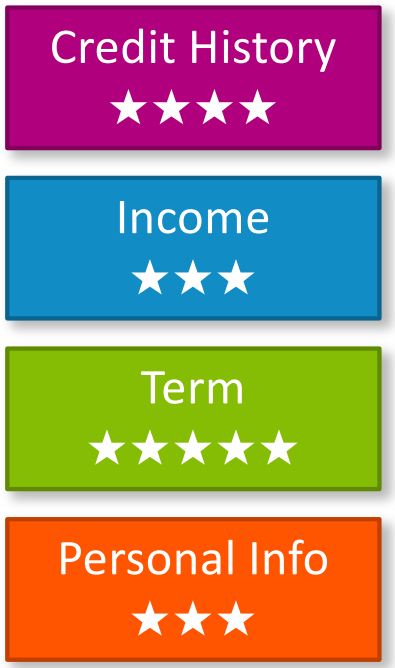
Example: excellent, good, or fair



Income

What's my income?

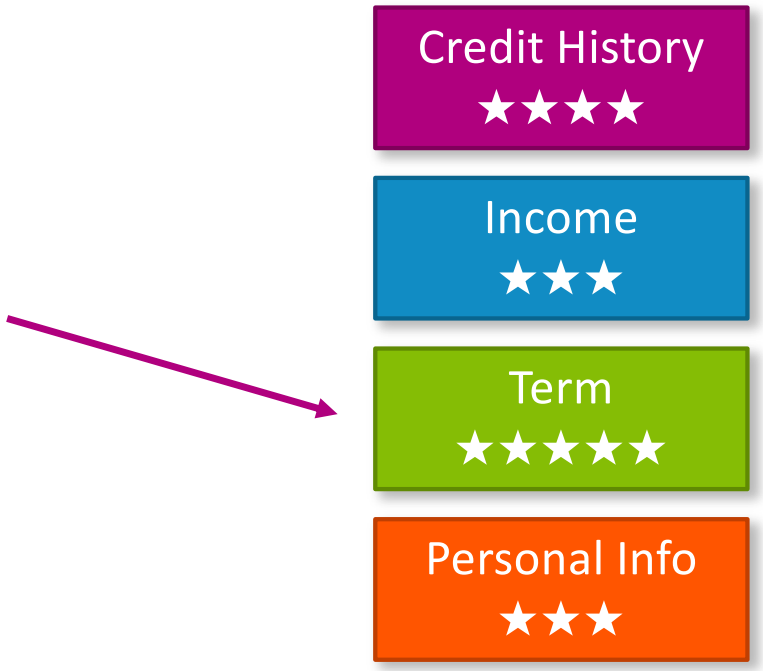
Example:
$80K per year



Loan terms

How soon do I need to pay the loan?

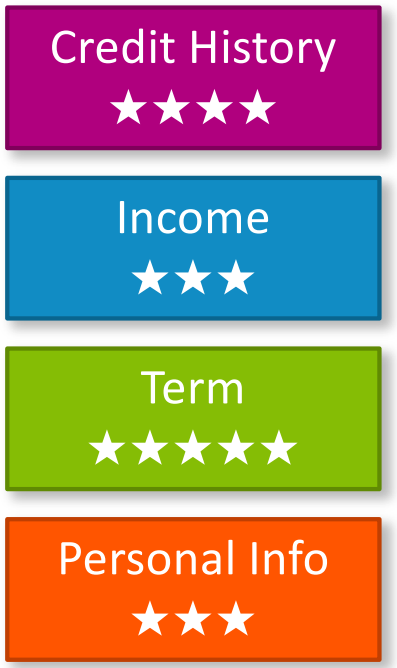
Example: 3 years, 5 years,…



Personal information

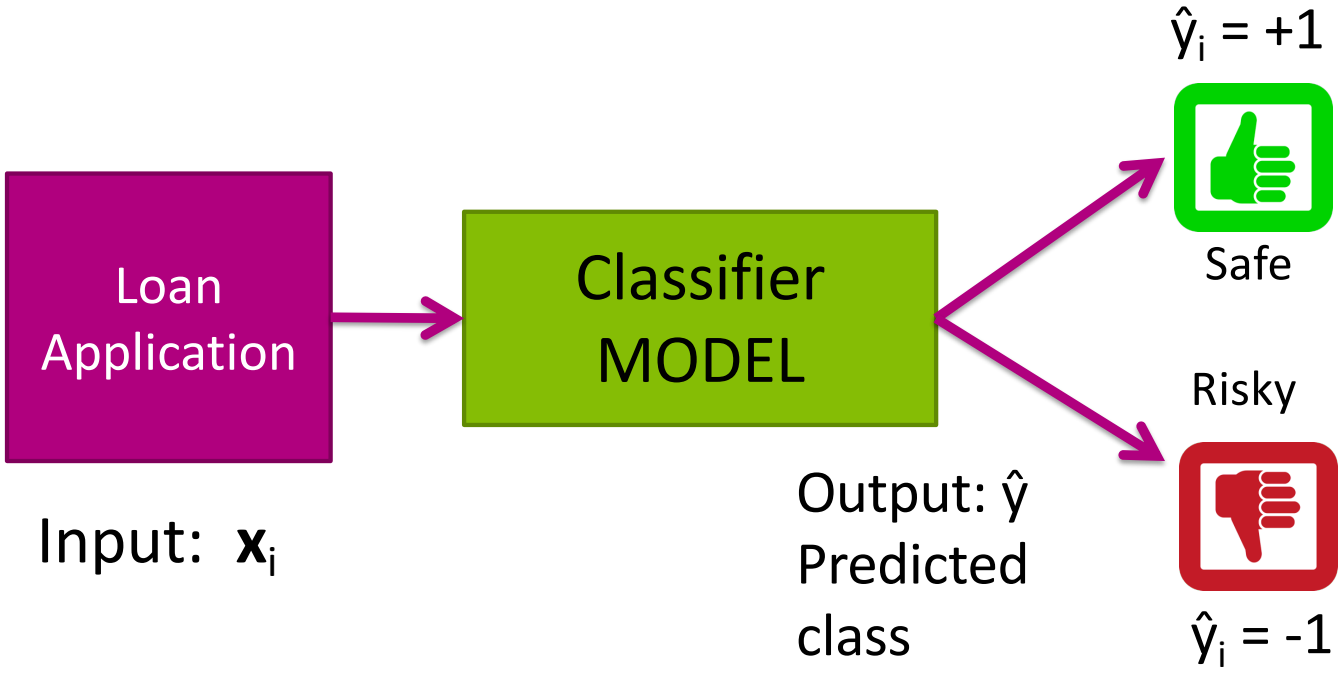
Age, reason for the loan, marital status,…

Example: Home loan for a married couple

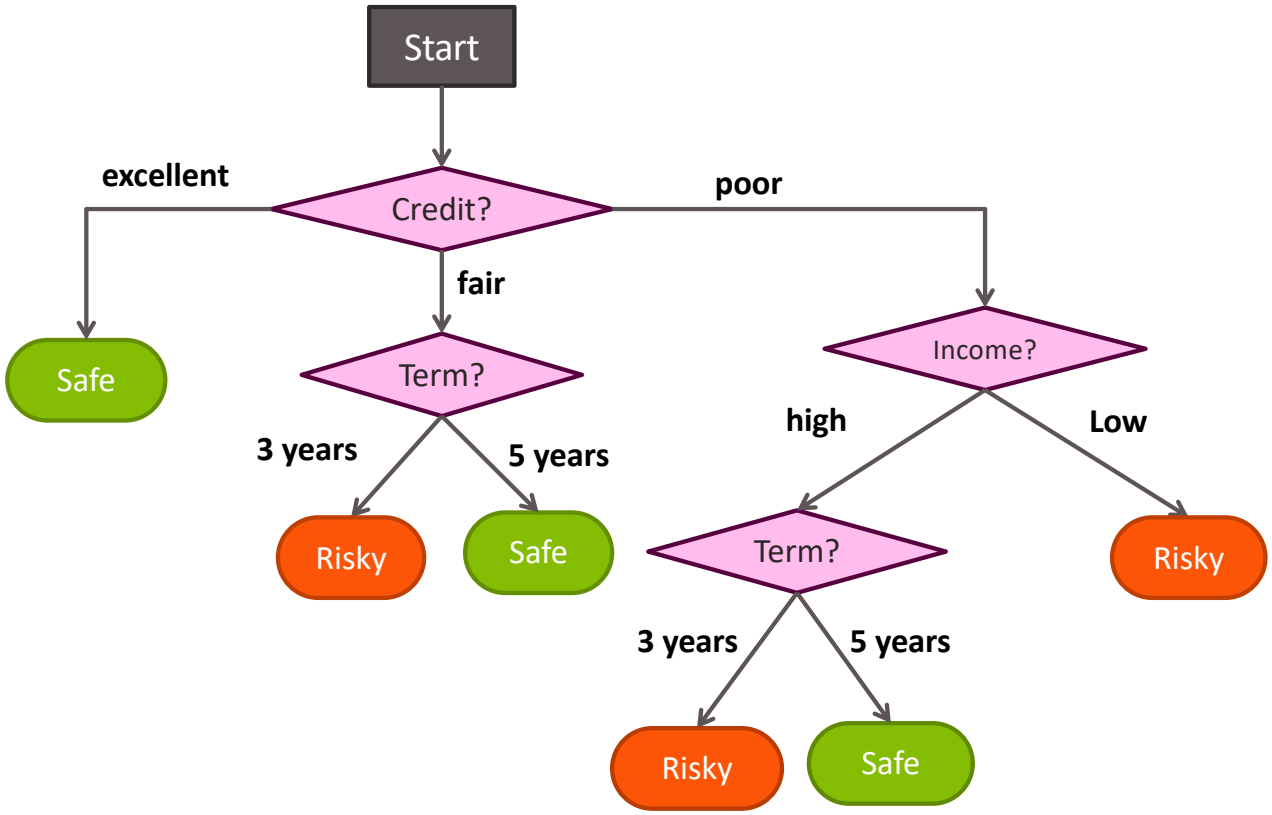


Intelligent application

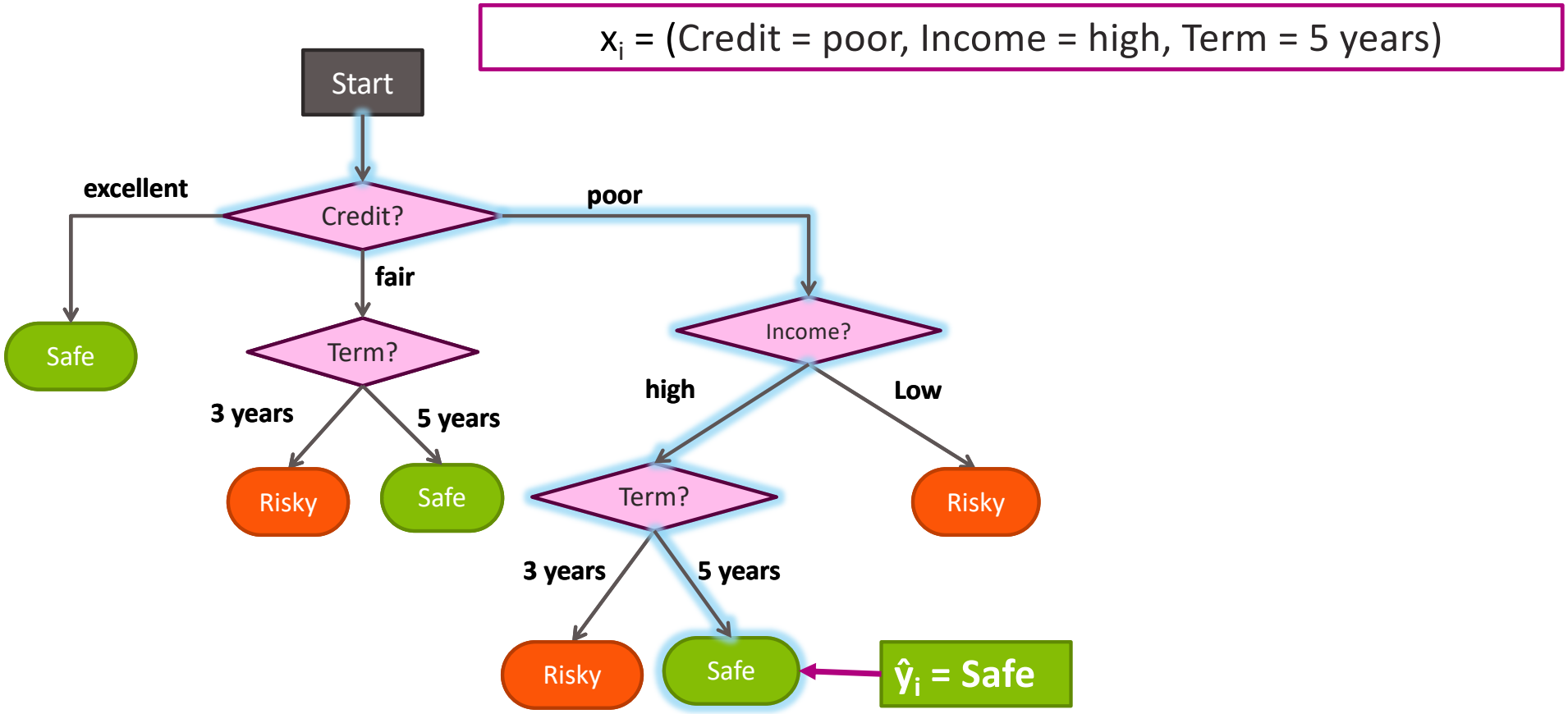
Classifier review



This module ... decision trees



Scoring a loan application

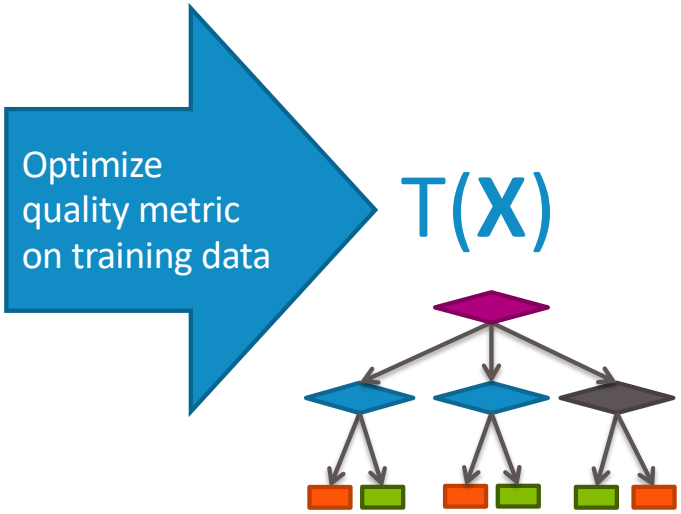


Decision tree learning task

Decision tree learning problem

Training data: N observations (x_i, y_i)

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



Quality metric: Classification error

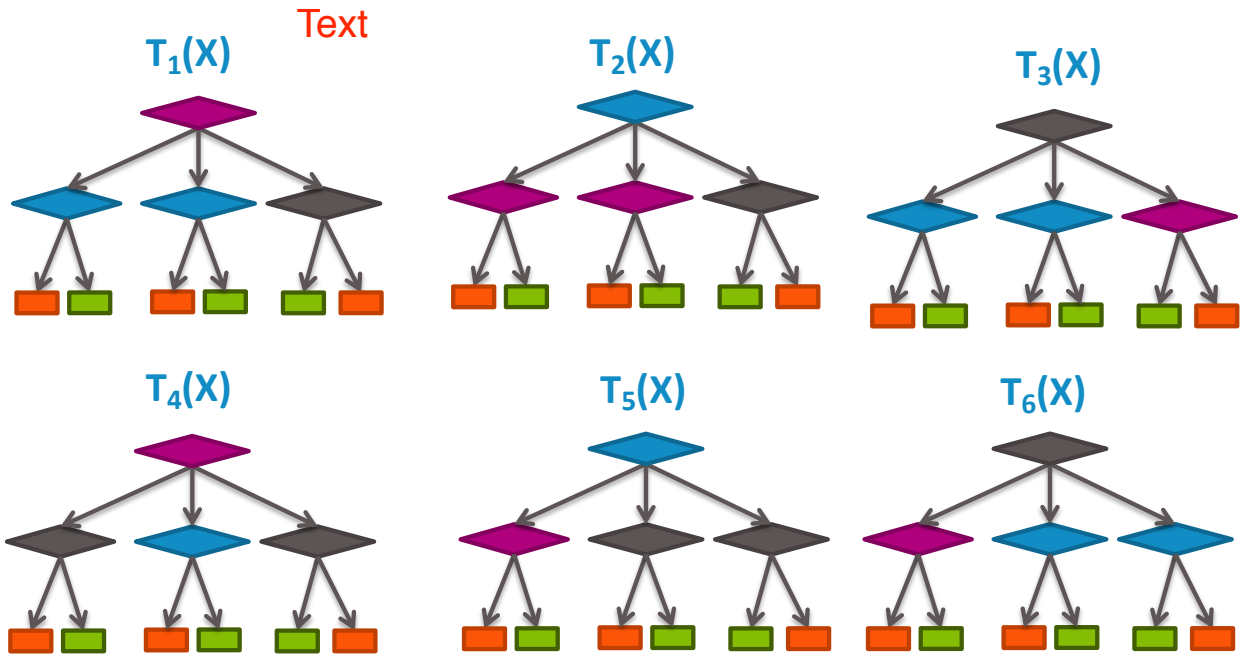
- Error measures fraction of mistakes

$$\text{Error} = \frac{\text{\# incorrect predictions}}{\text{\# examples}}$$

  - Best possible value : 0.0
  - Worst possible value: 1.0

How do we find the best tree?

Exponentially large number of possible trees makes decision tree learning hard!



Learning the smallest decision tree is an *NP-hard problem* [Hyafil & Rivest '76]

Greedy decision tree learning

we dont look for the best tree; use some heuristic that gets a tree that, most of the time, is good enough

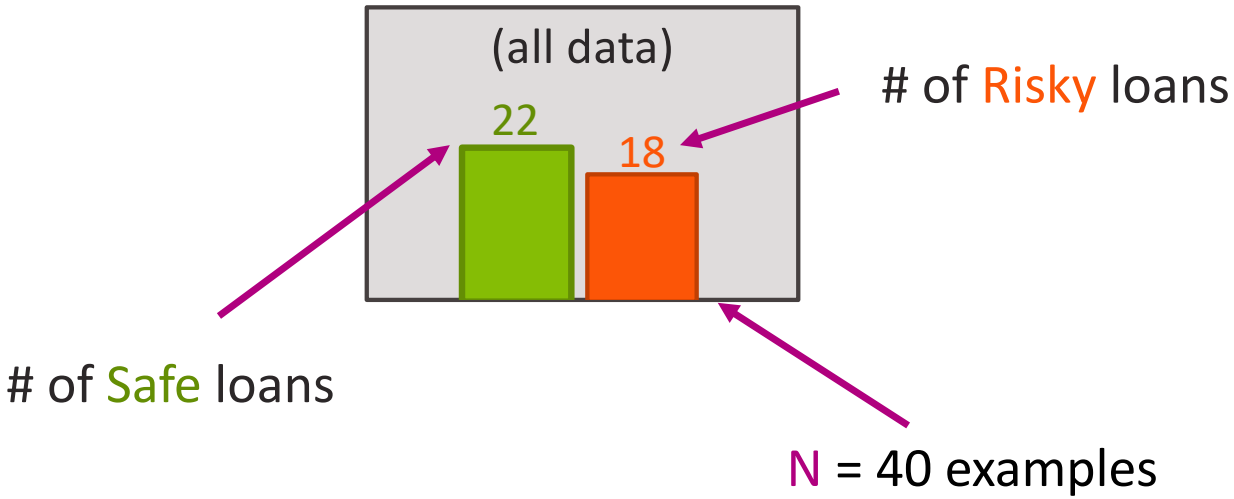
Our training data table

Assume N = 40, 3 features

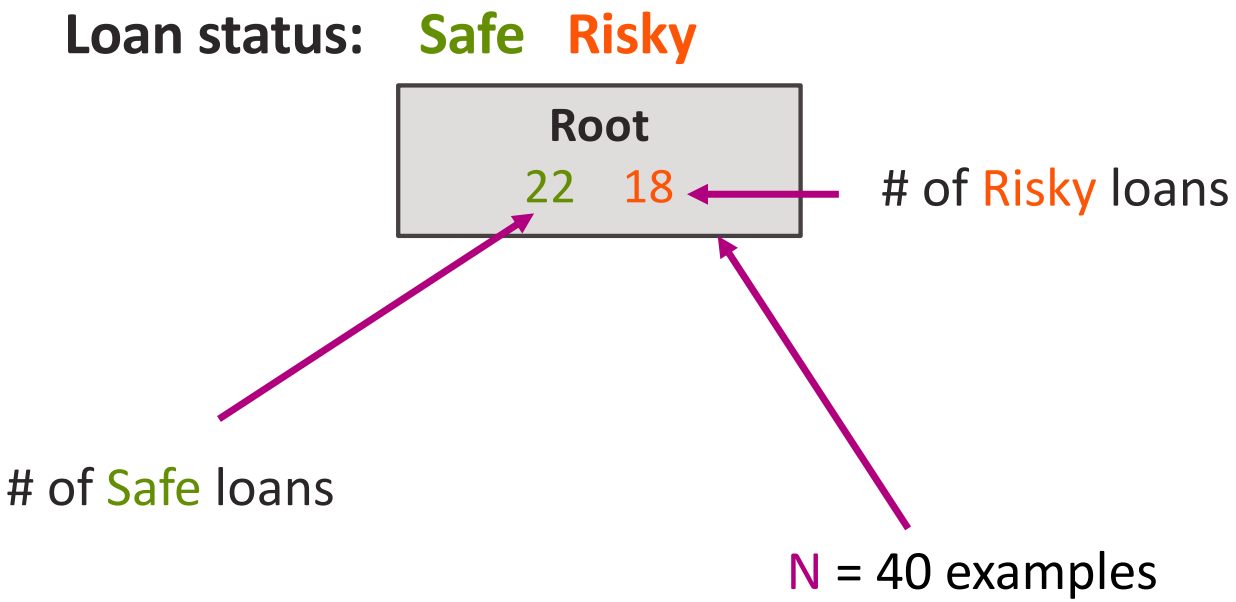
Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	5 yrs	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	risky
fair	5 yrs	low	safe
poor	3 yrs	high	risky
poor	5 yrs	low	safe
fair	3 yrs	high	safe

Start with all the data

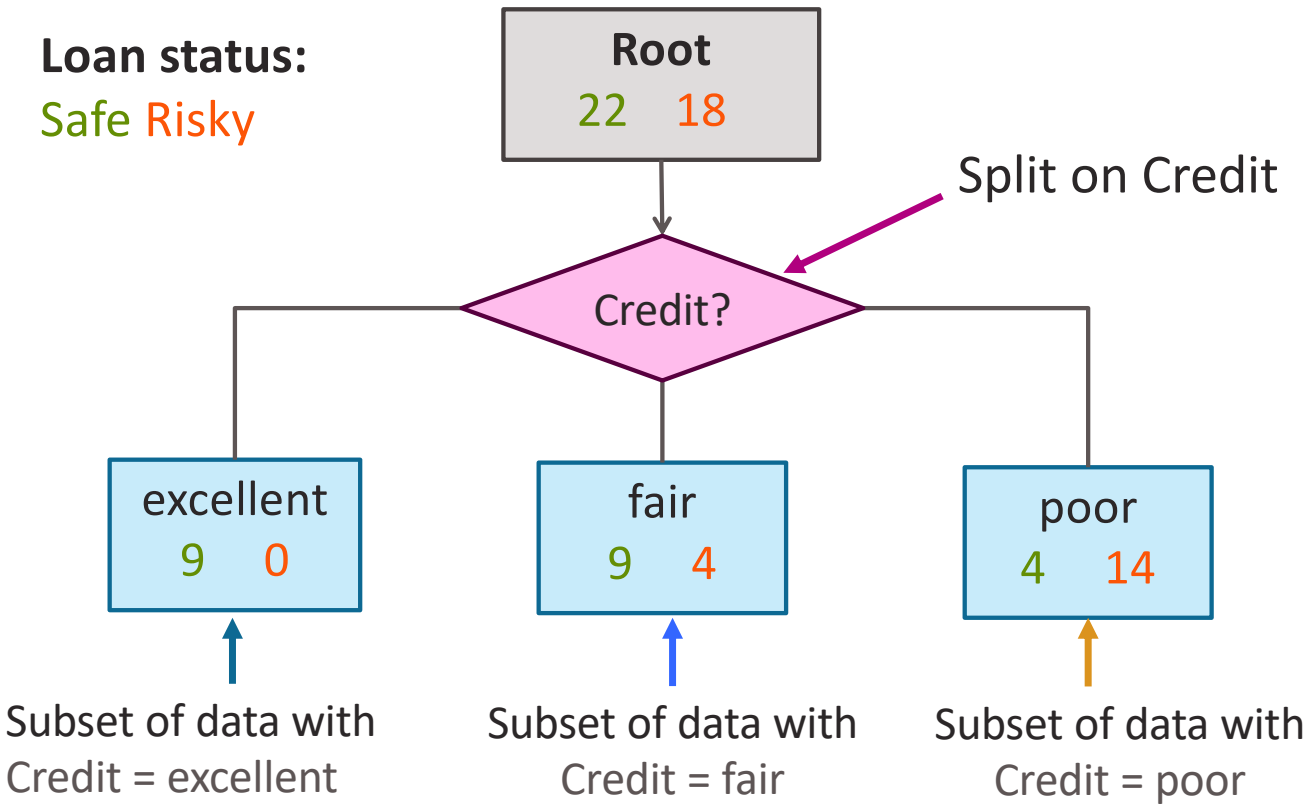
Loan status: Safe Risky



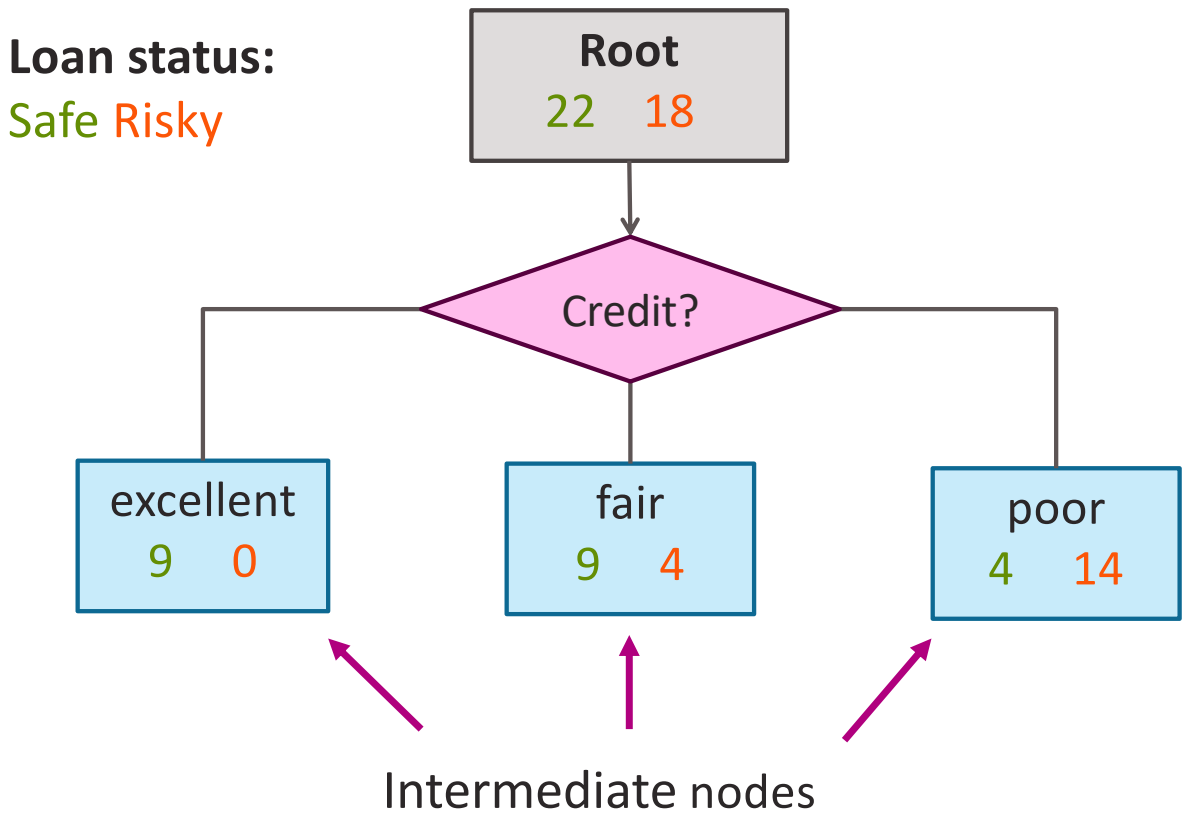
Compact visual notation: Root node



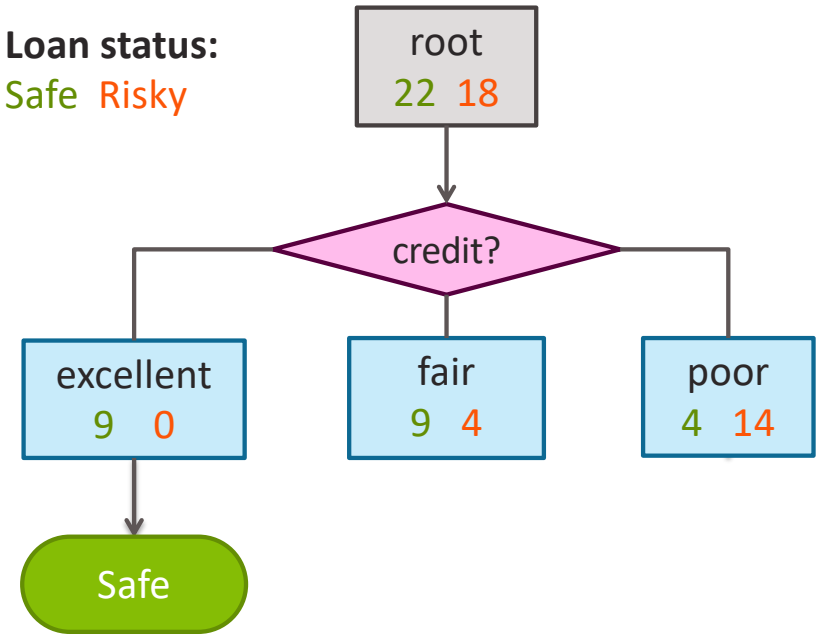
Decision stump: Single level tree



Visual notation: Intermediate nodes



Proceed to build a tree on each of children

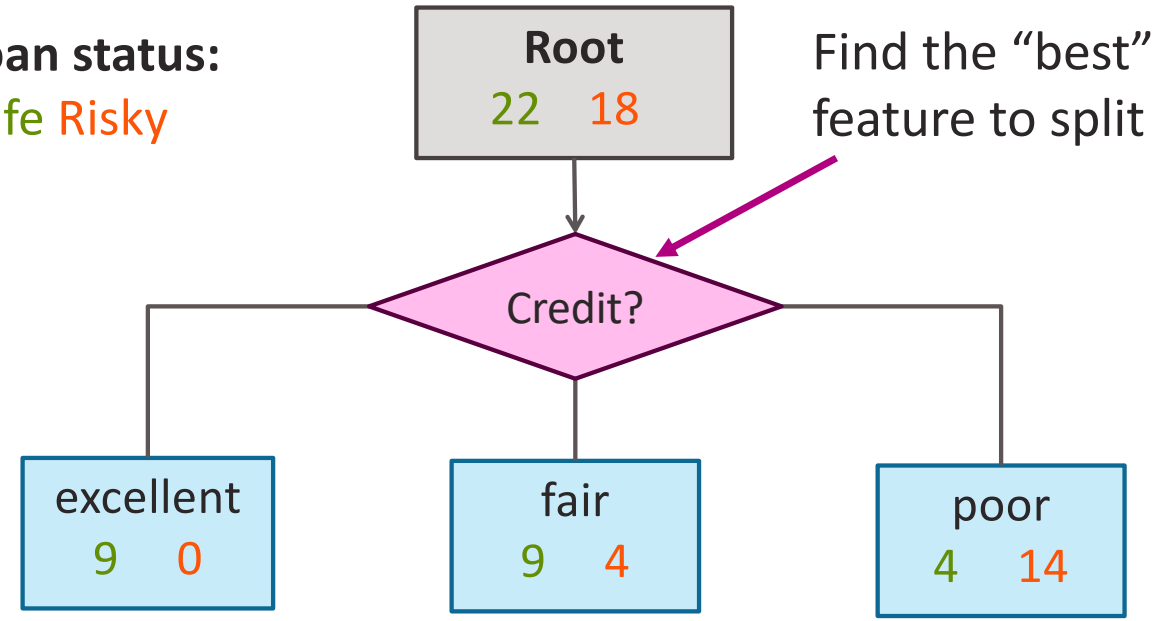


Selecting best feature to split on

which feature should we split on?

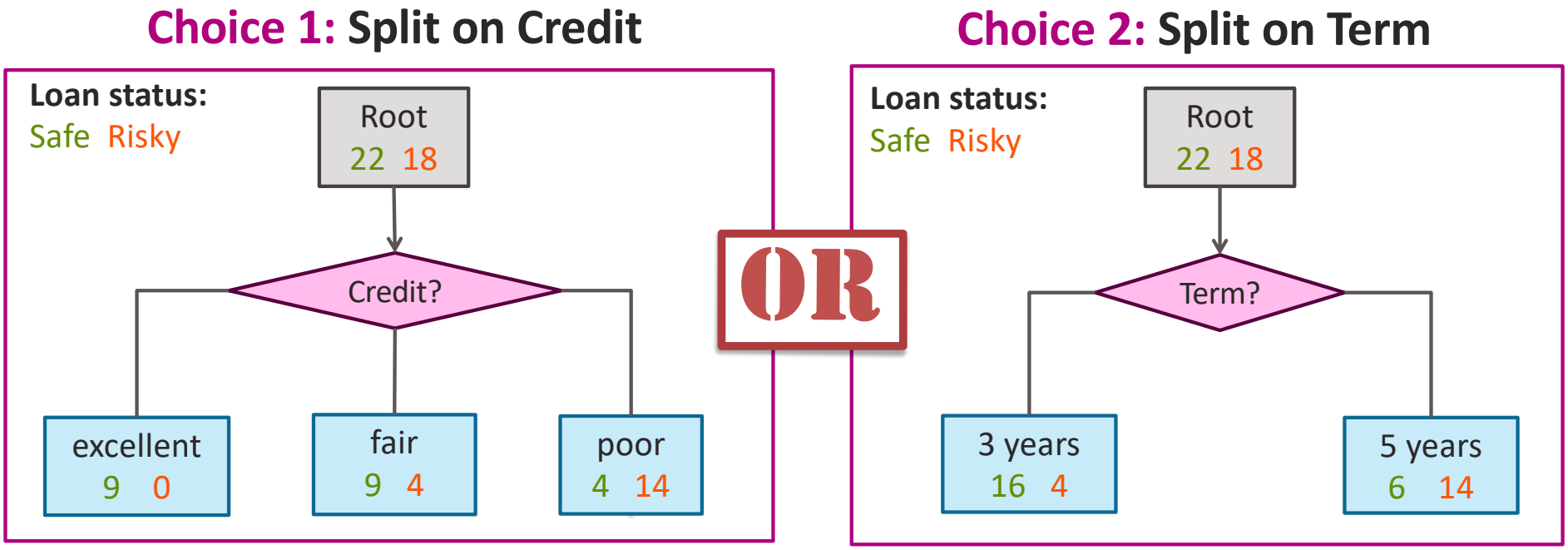
How do we pick our first split?

Loan status:
Safe Risky

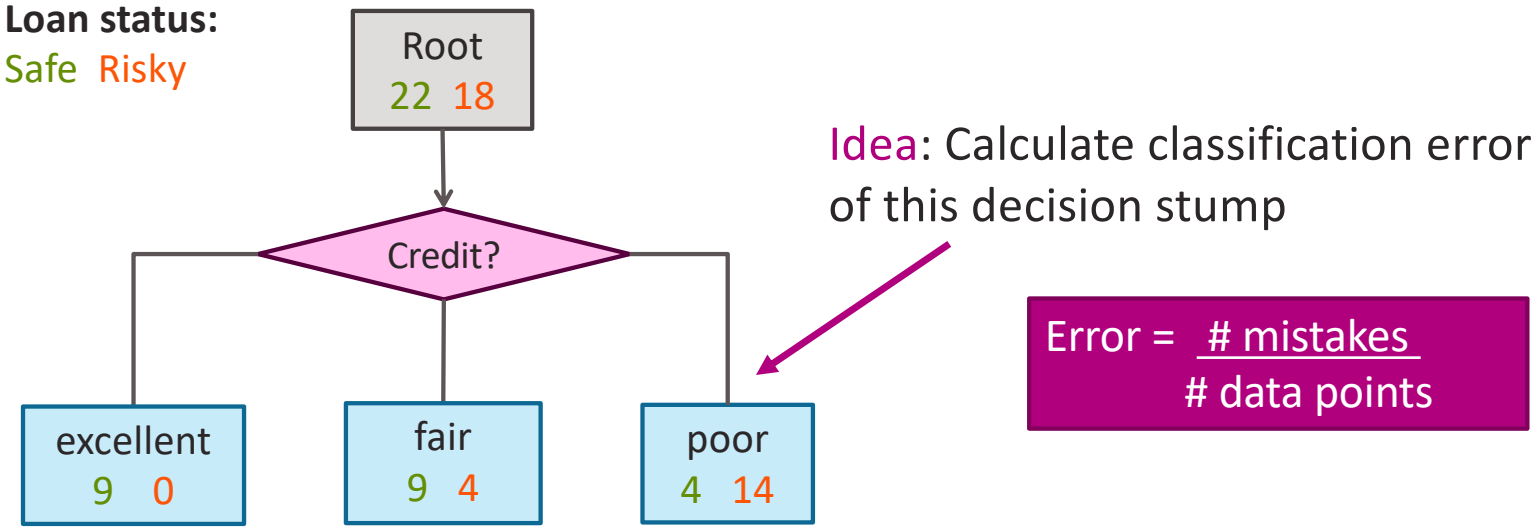


Find the "best" feature to split on!

How do we select the best feature?



How do we measure effectiveness of a split?



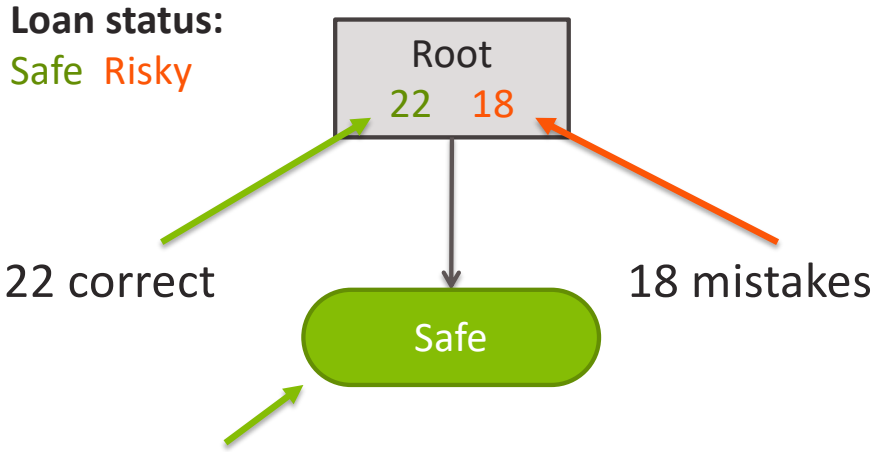
Idea: Calculate classification error of this decision stump

$$\text{Error} = \frac{\text{\# mistakes}}{\text{\# data points}}$$

stop right here; how many errors would we make?

Calculating classification error

- Step 1: $\hat{y}$ = class of majority of data in node
- Step 2: Calculate classification error of predicting $\hat{y}$ for this data

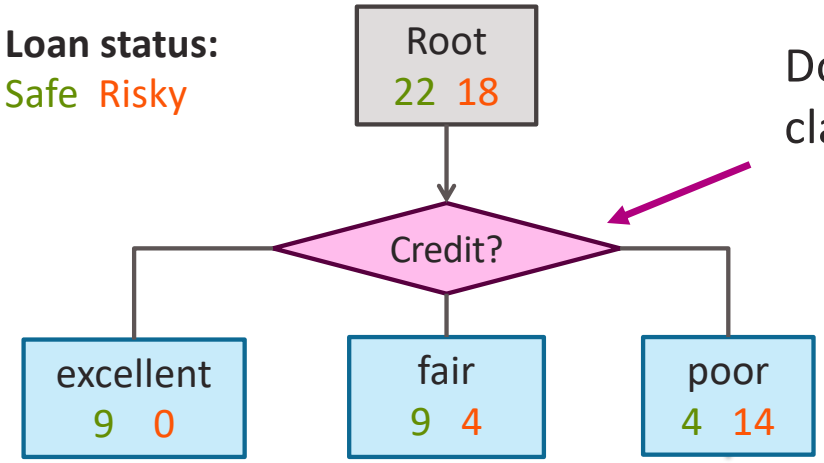


Tree	Classification error
(root)	0.45

predict whatever outcome is more common in training

Choice 1: Split on Credit history?

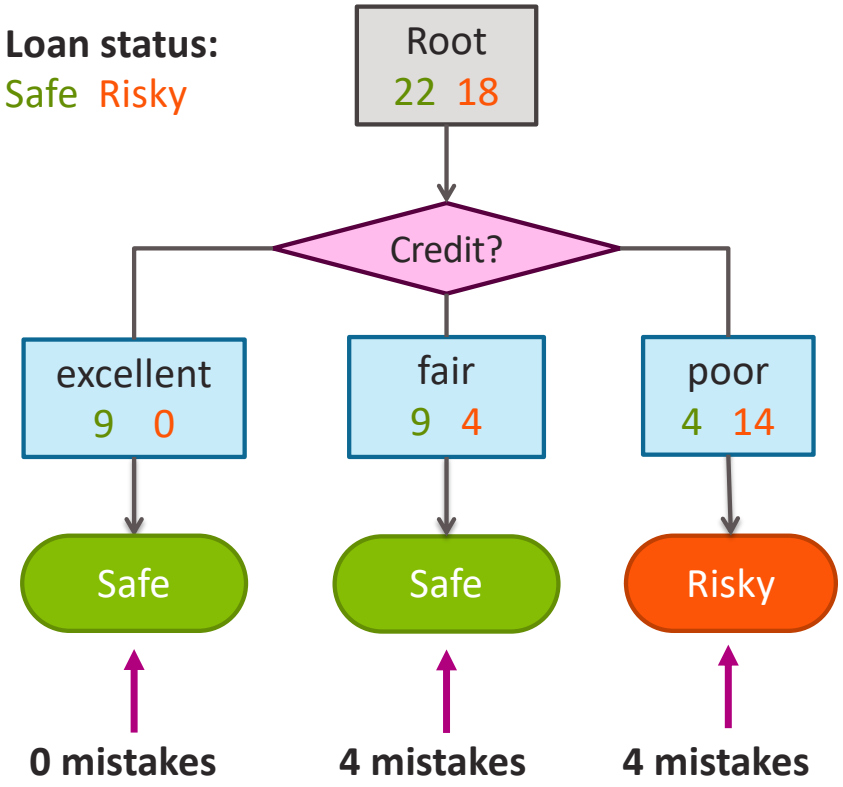
Choice 1: Split on Credit



Does a split on Credit reduce classification error below 0.45?

Split on Credit: Classification error

Choice 1: Split on Credit



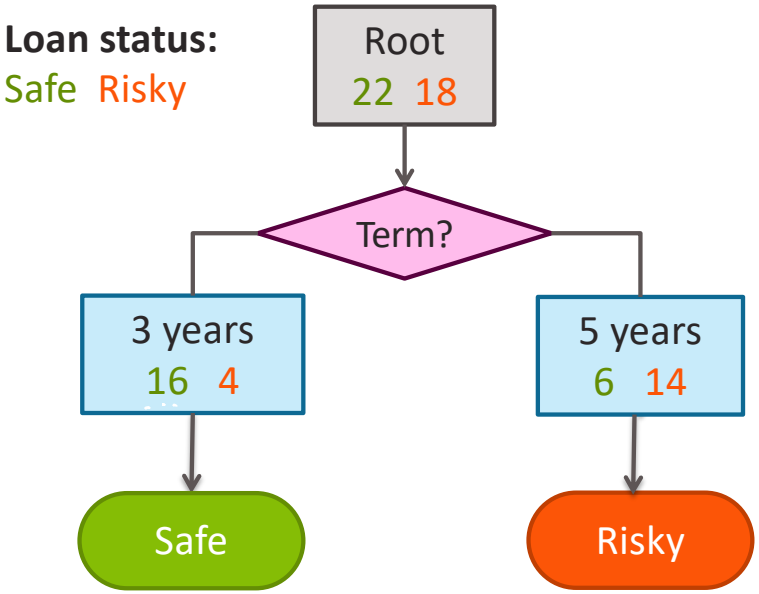
$$\text{Error} = \frac{4+4}{22+18} = 0.2$$

Tree	Classification error
(root)	just guess most common 0.45
Split on credit	0.2

Choose label that has the majority

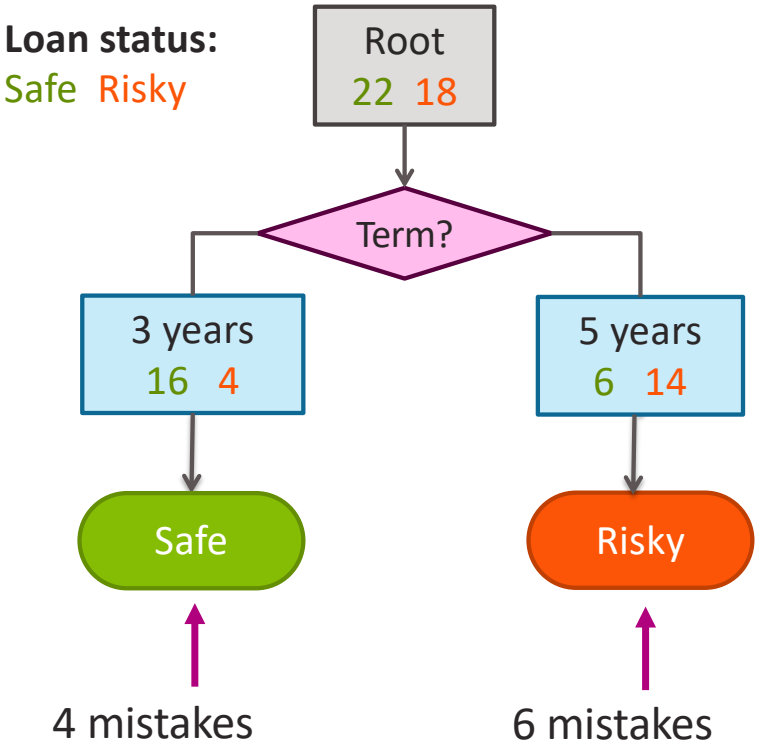
Choice 2: Split on Term?

Choice 2: Split on Term



Evaluating the split on Term

Choice 2: Split on Term



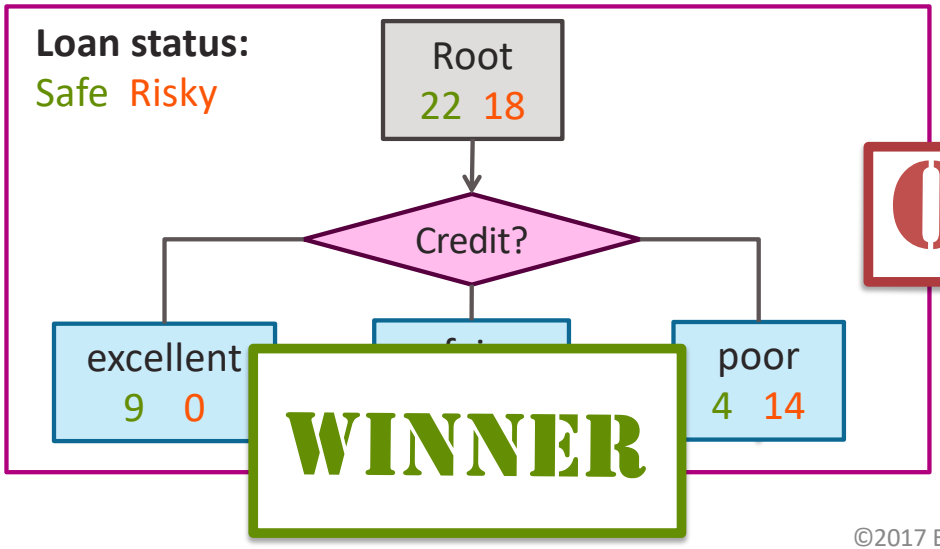
$$\text{Error} = \frac{4+6}{40} = 0.25$$

Tree	Classification error
(root)	0.45
Split on credit	0.2
Split on term	0.25

Choice 1 vs Choice 2: Comparing split on Credit vs Term

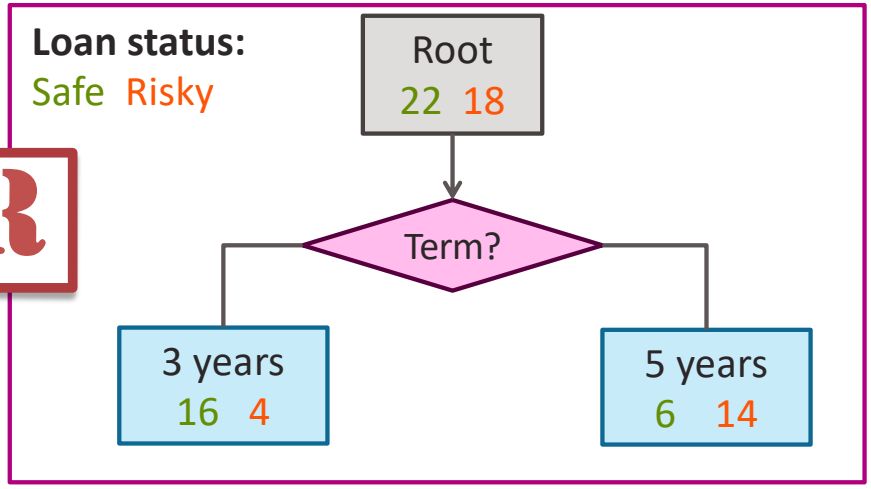
Tree	Classification error
(root)	0.45
split on credit	0.2
split on loan term	0.25

Choice 1: Split on Credit



OR

Choice 2: Split on Term

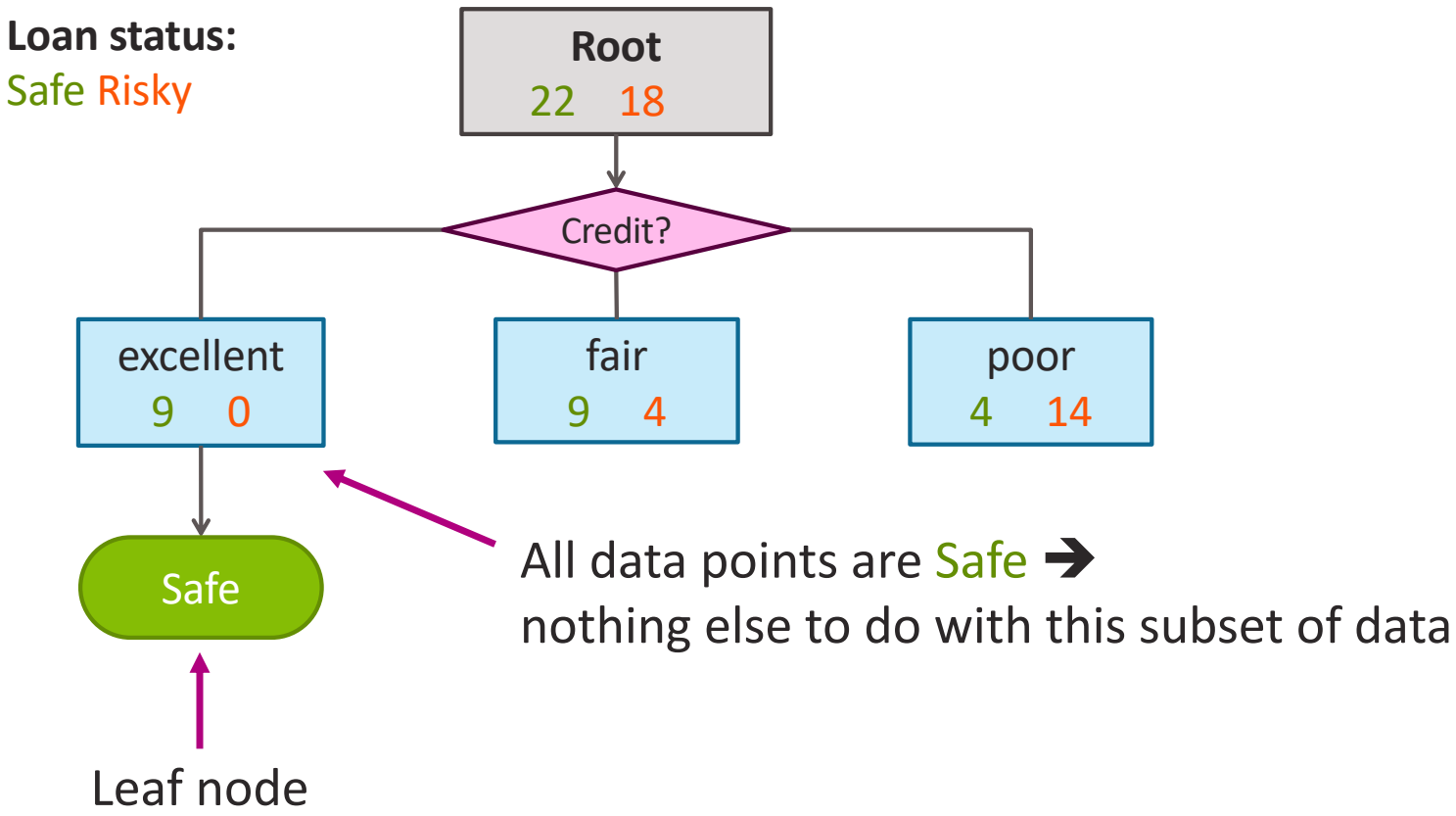


Feature split selection algorithm

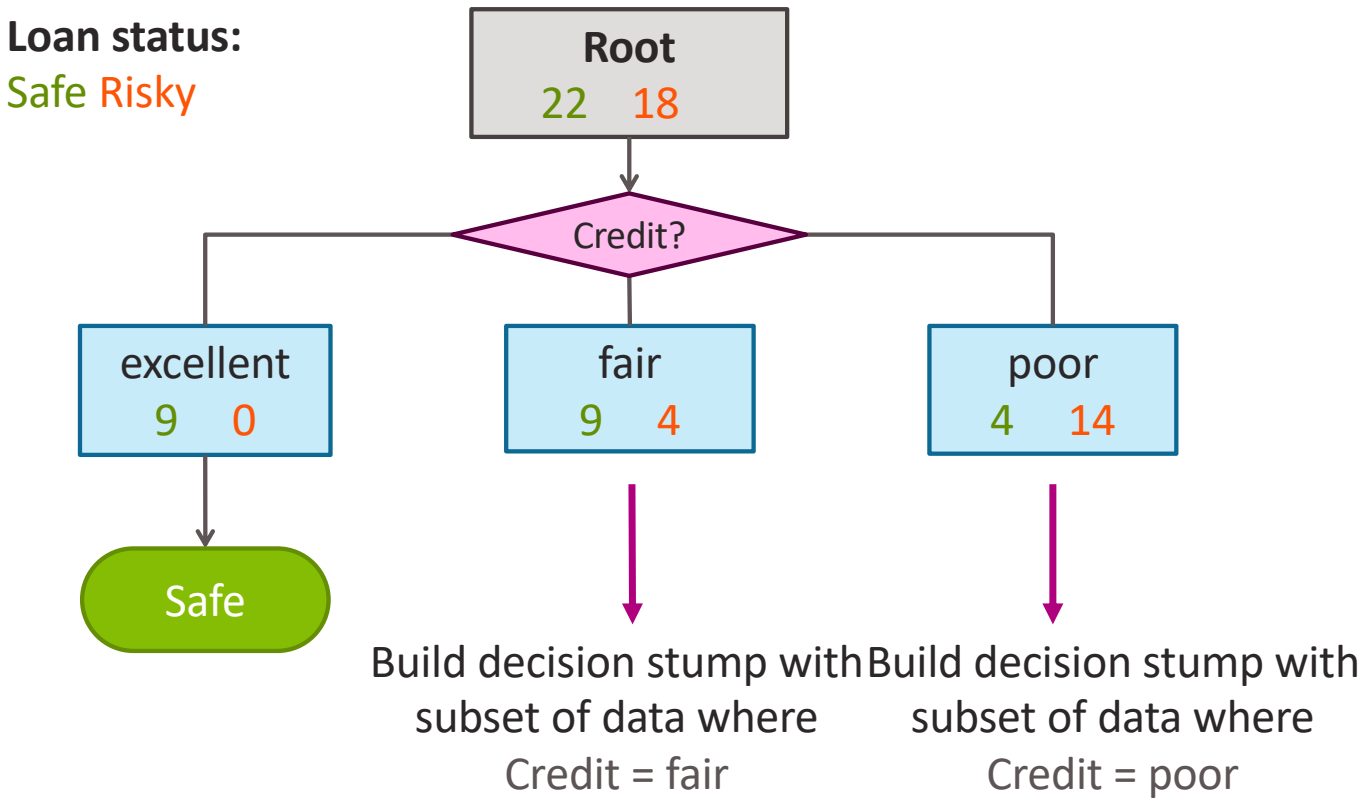
- Given a subset of data M (a node in a tree)
- For each feature $\phi_i(x)$:
  1. Split data of M according to feature $\phi_i(x)$
  2. Compute classification error split
- Chose feature $\phi^*(x)$ with lowest classification error

Recursion & Stopping conditions

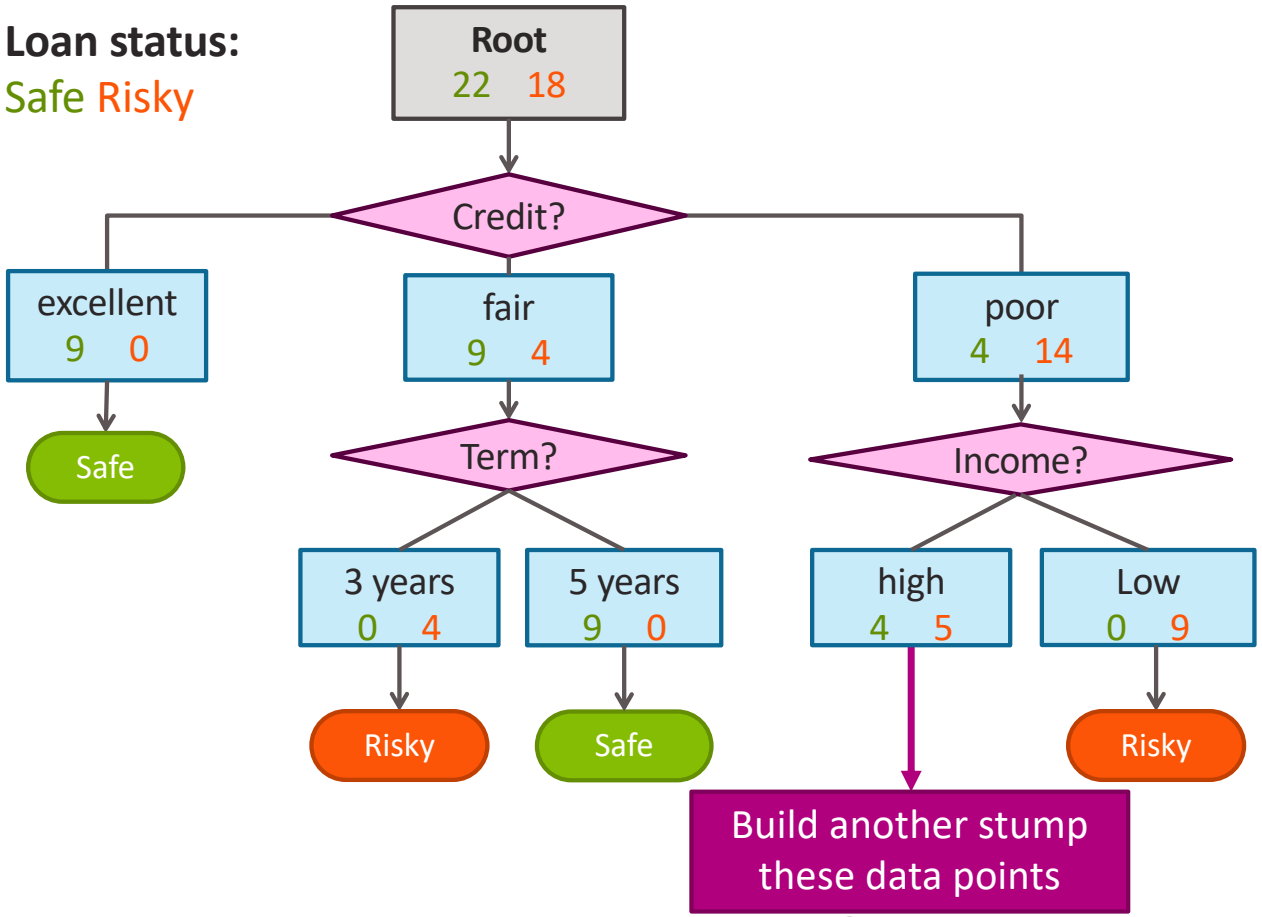
We've learned a decision stump, what next?



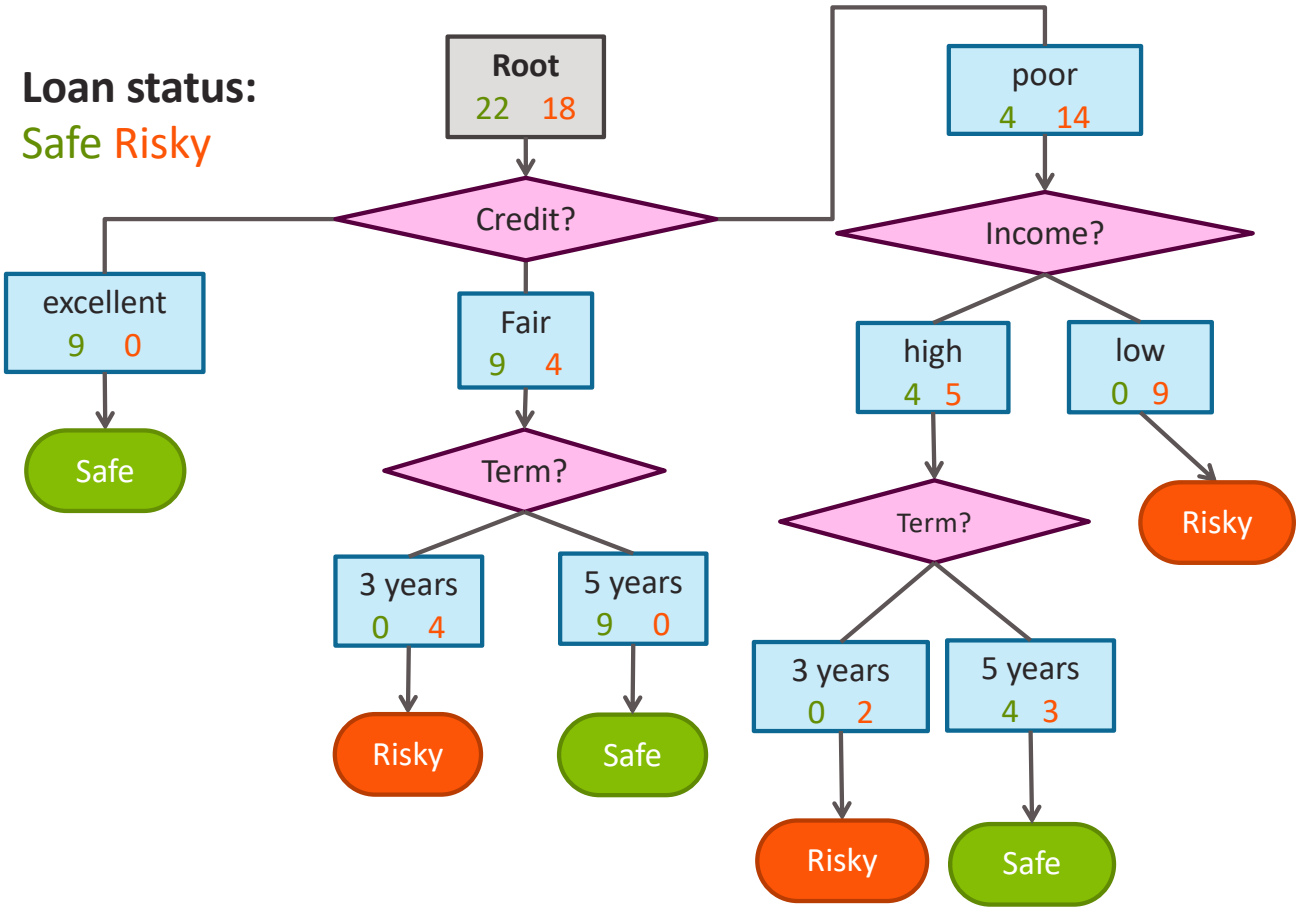
Tree learning = Recursive stump learning



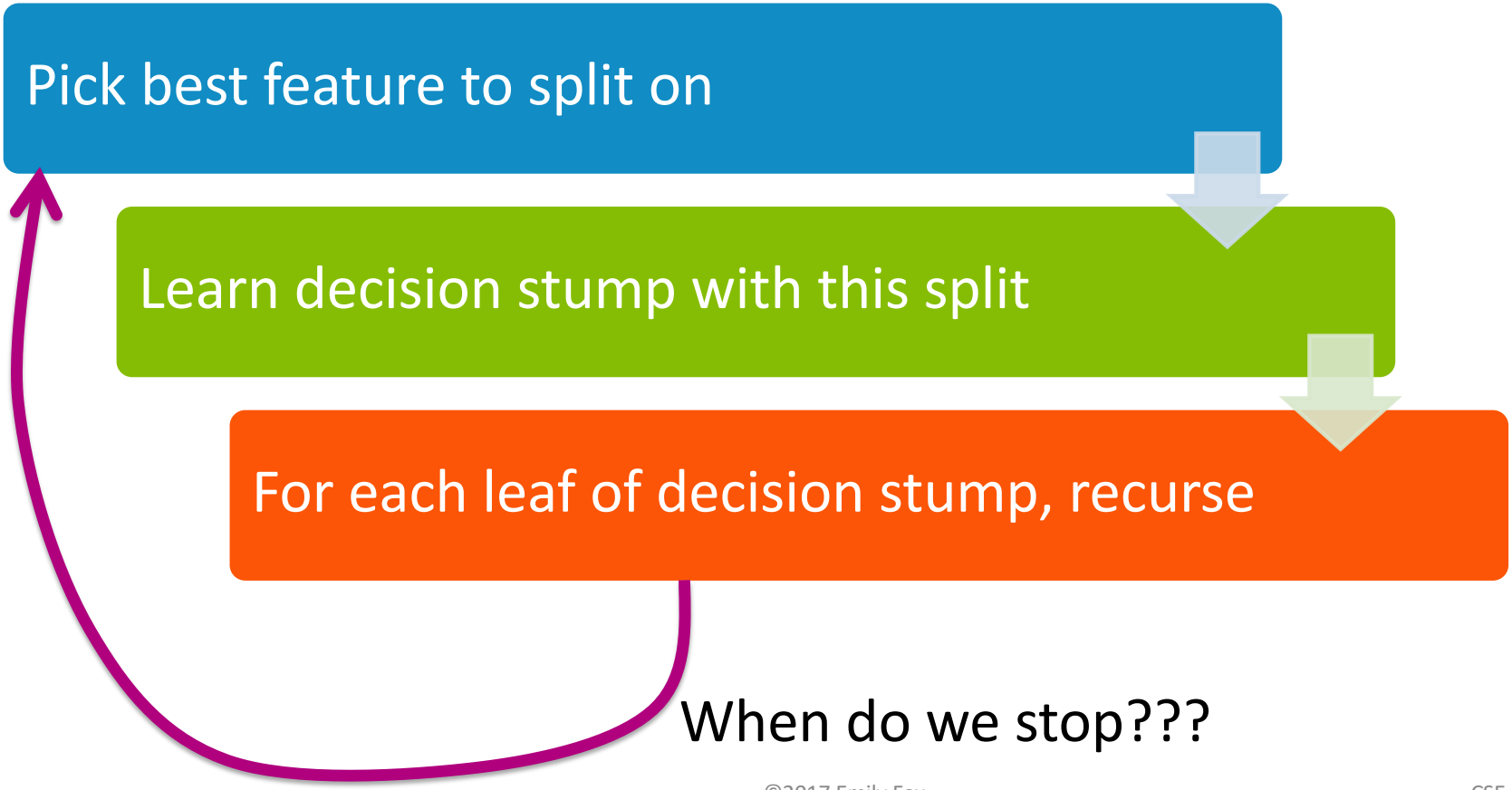
Second level



Final decision tree

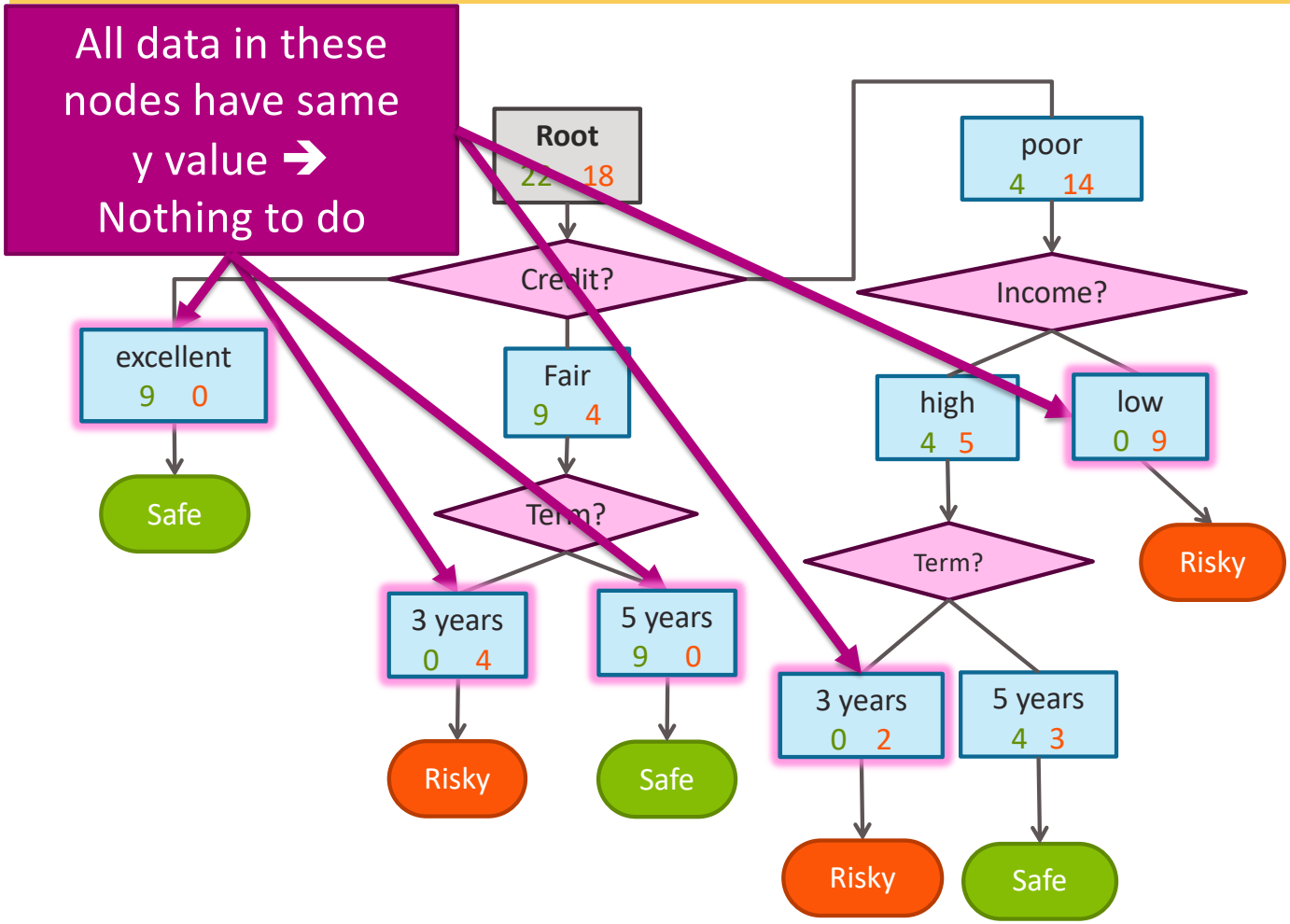


Simple greedy decision tree learning



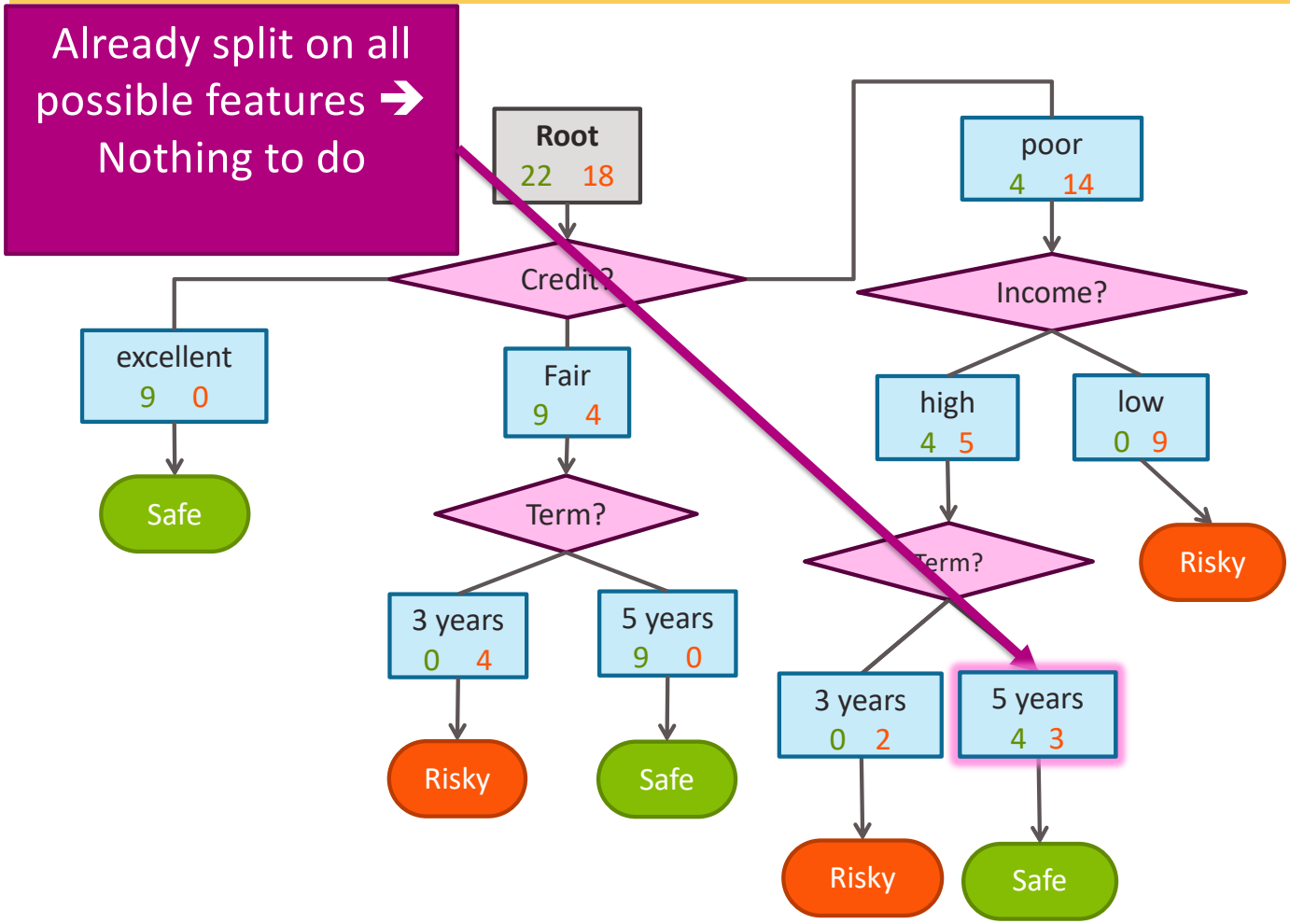
Stopping condition 1: All data agrees on y

All data in these nodes have same y value ➔ Nothing to do



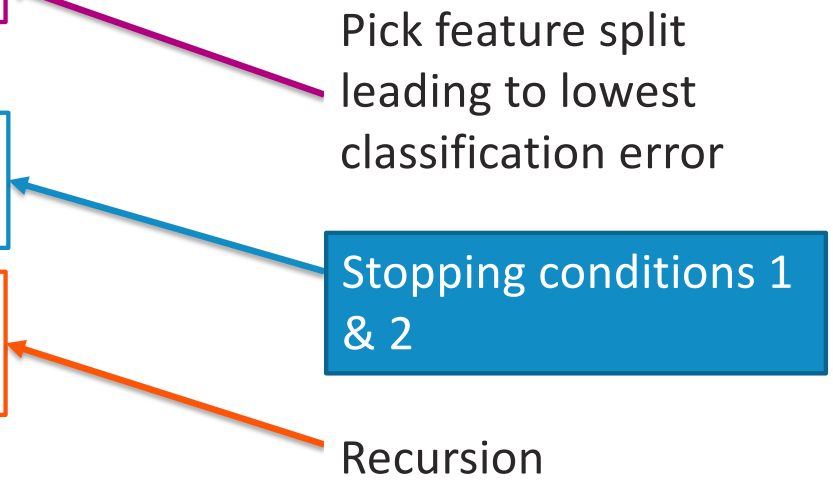
Stopping condition 2: Already split on all features

Already split on all possible features ➔ Nothing to do

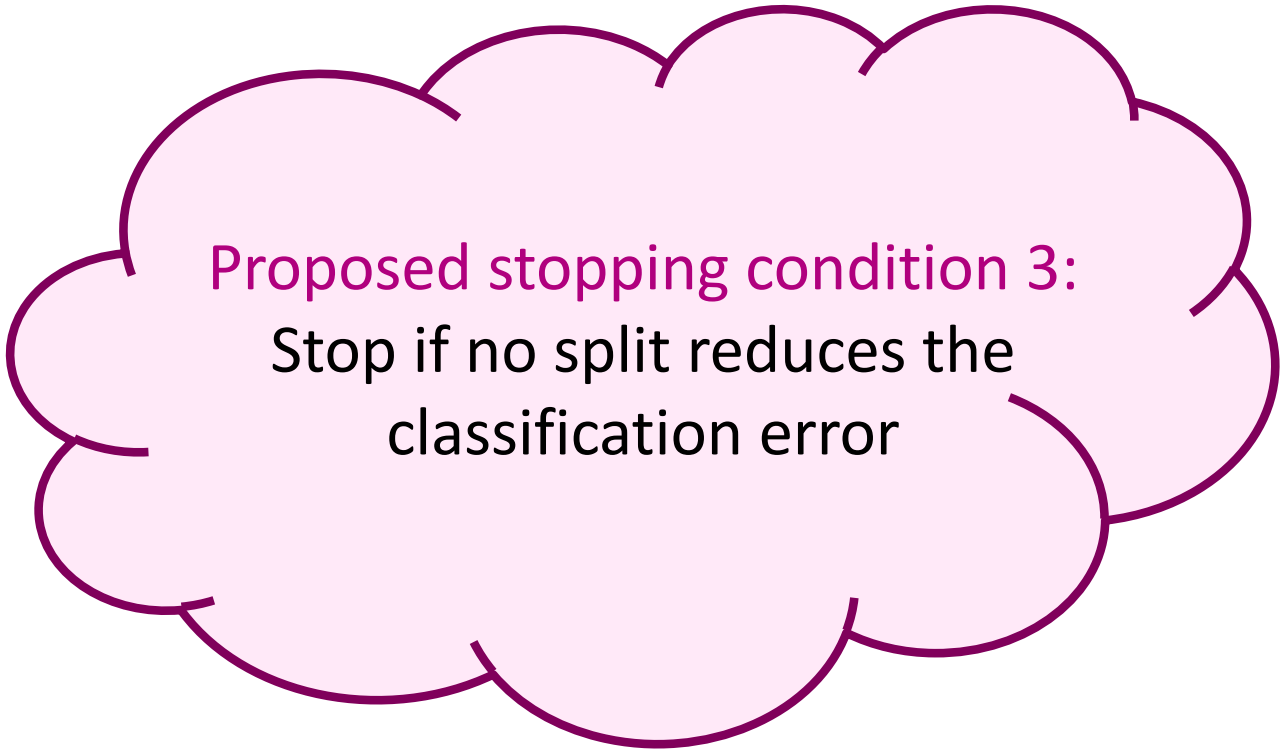


Greedy decision tree learning

- 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 do, make predictions
  - Step 4: Otherwise, go to Step 2 & continue (recurse) on this split



Is this a good idea?



Stopping condition 3:

Don't stop if error doesn't decrease???

y = x[1] xor x[2]

x[1]	x[2]	y
False	False	False
False	True	True
True	False	True
True	True	False

y values
True False

Root
2 2

Error = $\frac{2}{4}$ = 0.5

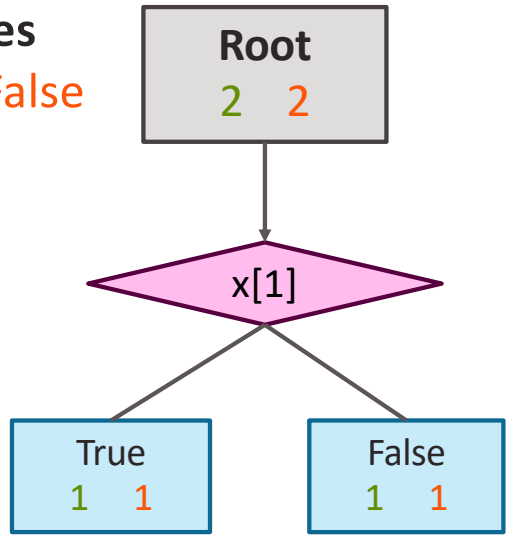
Tree	Classification error
(root)	0.5

Consider split on x[1]

y = x[1] xor x[2]

x[1]	x[2]	y
False	False	False
False	True	True
True	False	True
True	True	False

y values
True False



$$\text{Error} = \frac{2}{4} = 0.5$$

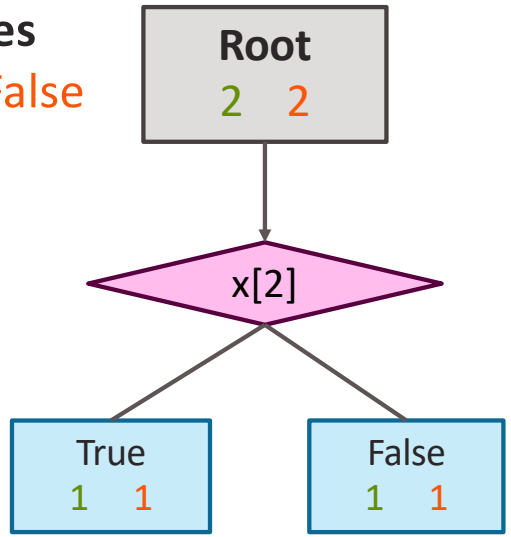
Tree	Classification error
(root)	0.5
Split on x[1]	0.5

Consider split on x[2]

y = x[1] xor x[2]

x[1]	x[2]	y
False	False	False
False	True	True
True	False	True
True	True	False

y values
True False



Error = $\frac{2}{4}$ = 0.5

Neither features improve training error… Stop now???

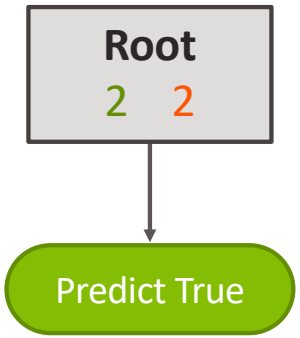
Tree	Classification error
(root)	0.5
Split on x[1]	0.5
Split on x[2]	0.5

Final tree with stopping condition 3

y = x[1] xor x[2]

x[1]	x[2]	y
False	False	False
False	True	True
True	False	True
True	True	False

y values
True False



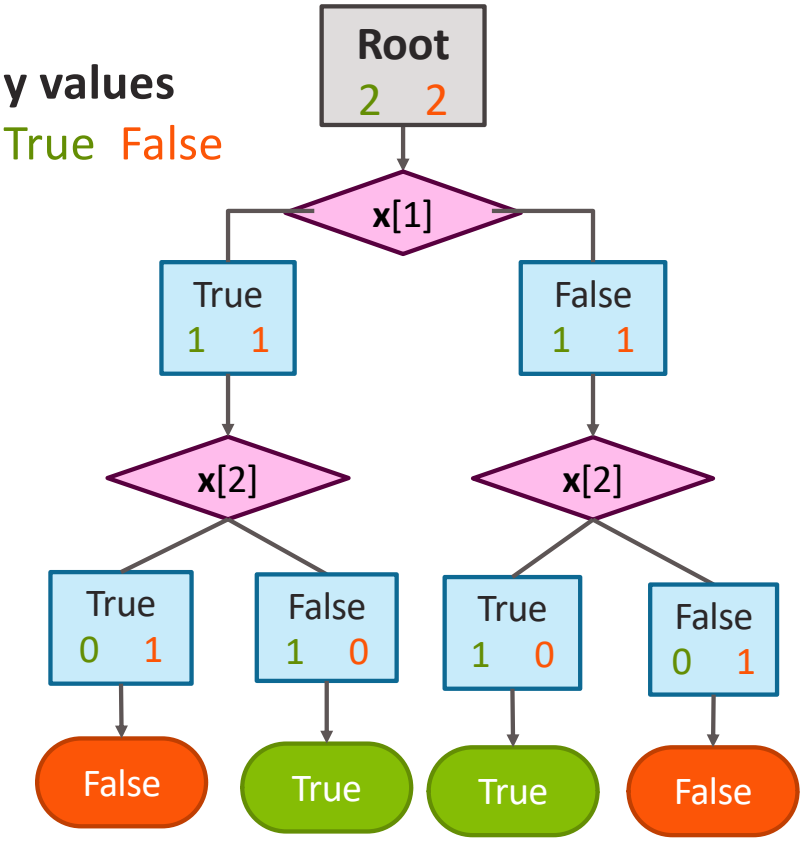
Tree	Classification error
with stopping condition 3	0.5

Without stopping condition 3

Condition 3 (stopping when training error doesn't improve) not always recommended!

y = x[1] xor x[2]

x[1]	x[2]	y
False	False	False
False	True	True
True	False	True
True	True	False



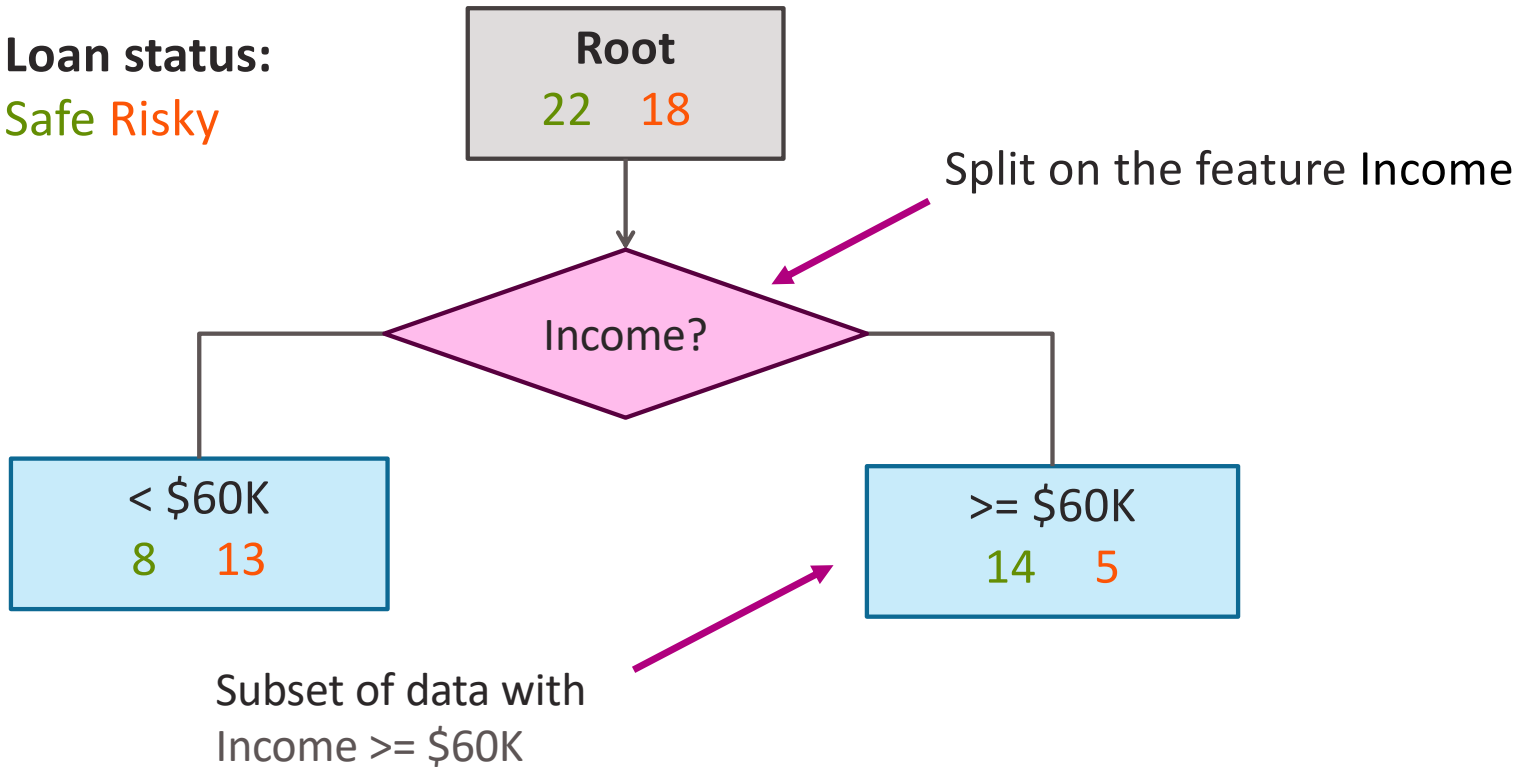
Tree	Classification error
with stopping condition 3	0.5
without stopping condition 3	0

Decision tree learning:
Real valued features

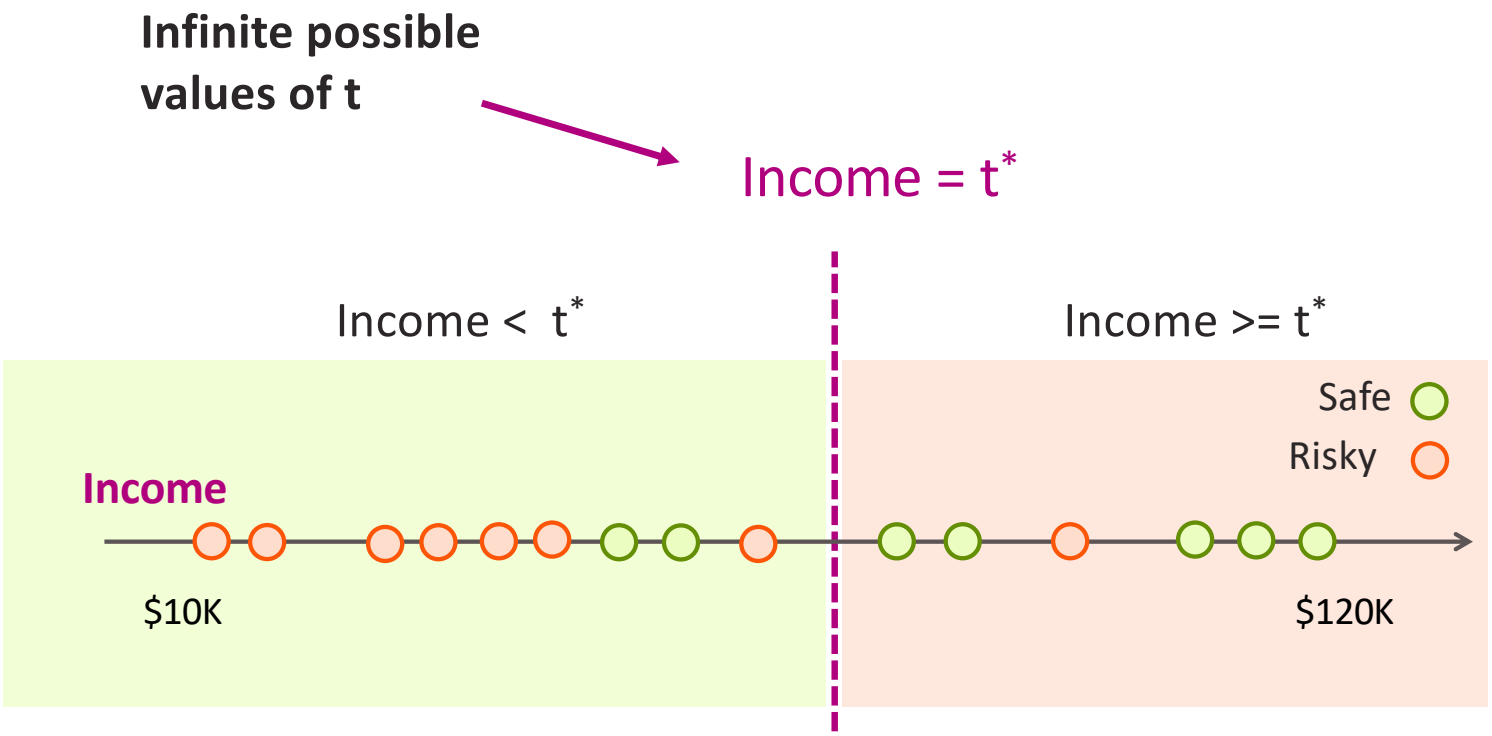
How do we use real values inputs?

Income	Credit	Term	y
$105 K	excellent	3 yrs	Safe
$112 K	good	5 yrs	Risky
$73 K	fair	3 yrs	Safe
$69 K	excellent	5 yrs	Safe
$217 K	excellent	3 yrs	Risky
$120 K	good	5 yrs	Safe
$64 K	fair	3 yrs	Risky
$340 K	excellent	5 yrs	Safe
$60 K	good	3 yrs	Risky

Threshold split (input is above or below some threshold; for real-valued features)

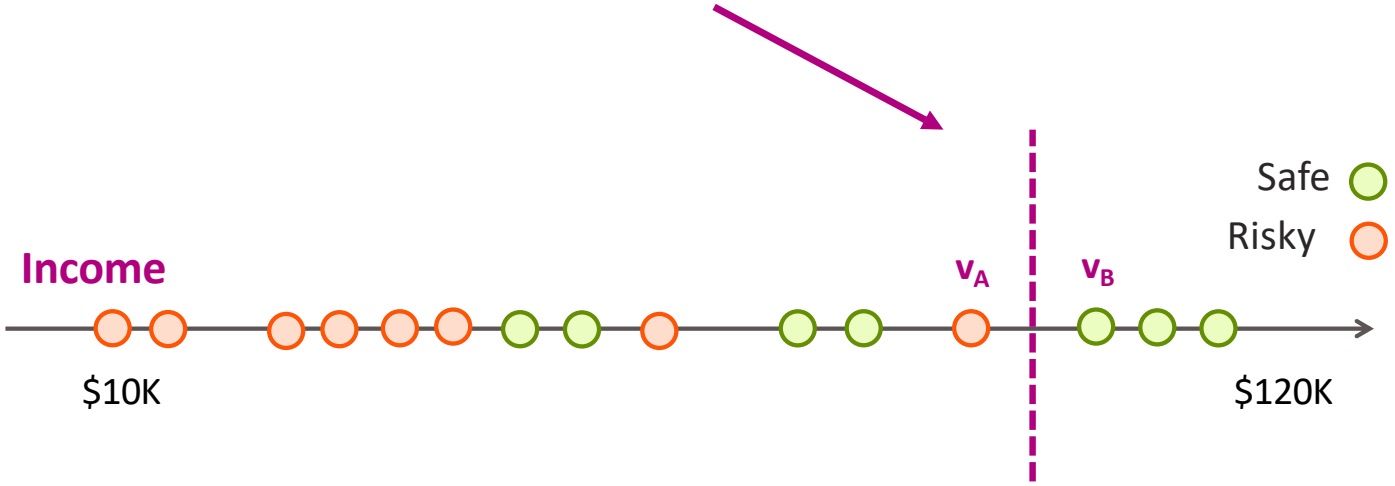


Finding the best threshold split



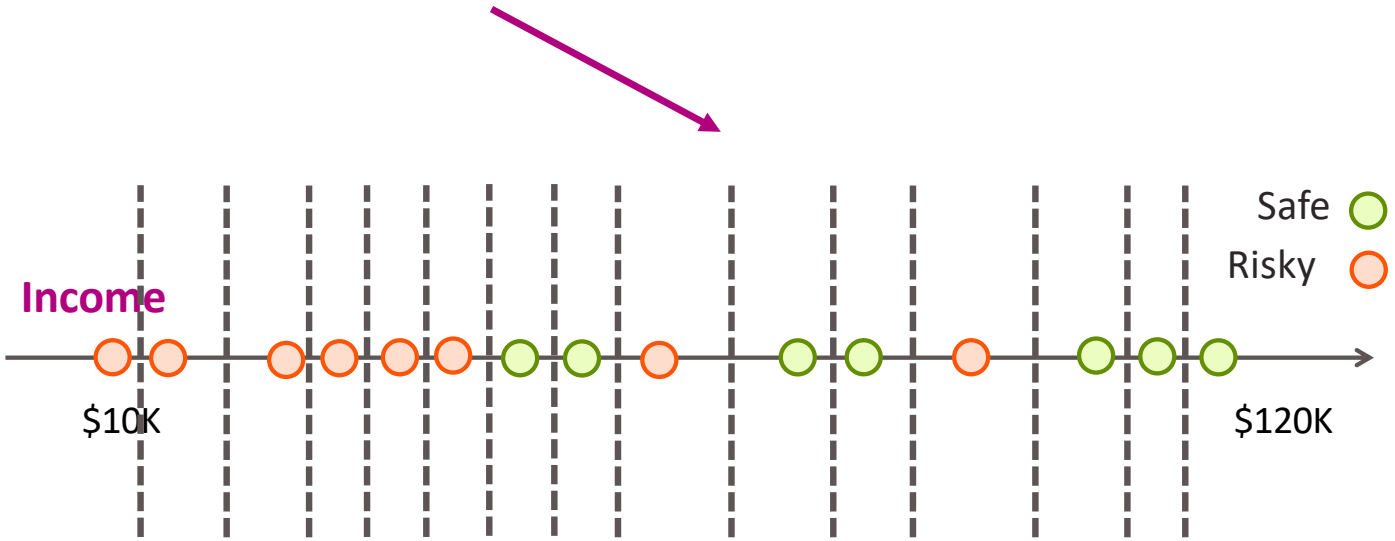
Consider a threshold between points

Same classification error for any threshold split between v_A and v_B



Only need to consider mid-points

Finite number of splits
to consider



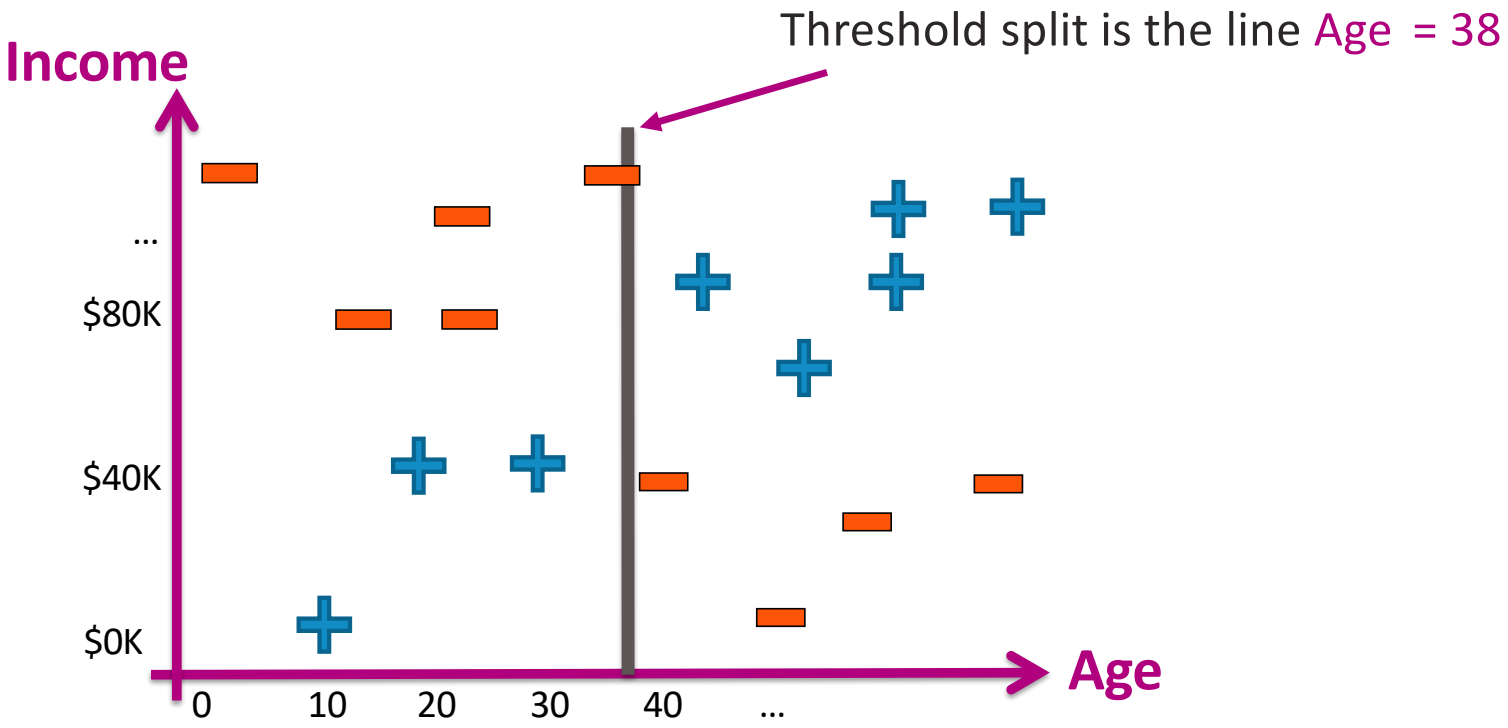
Threshold split selection algorithm

- Step 1: Sort the values of a feature $h_j(x)$:

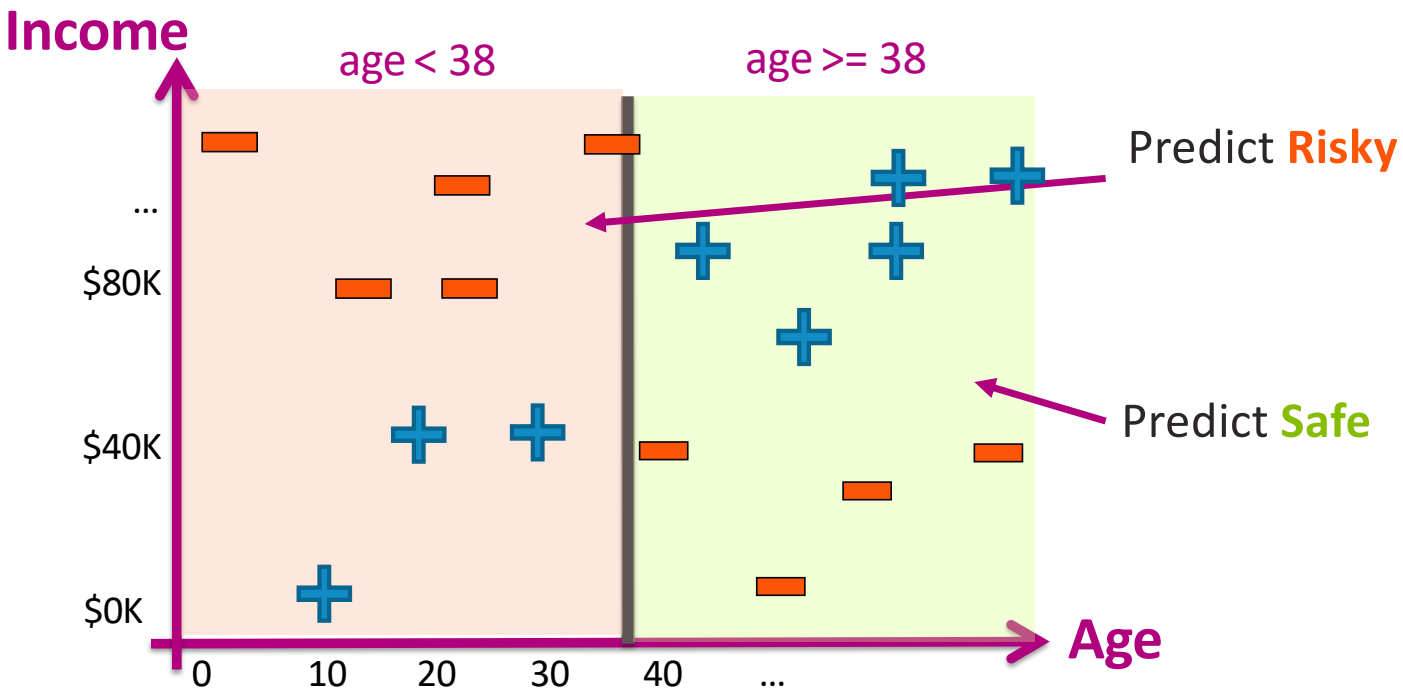
  Let $\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \ldots \mathbf{v}_N\}$ denote sorted values

- Step 2:
  - For i = 1 … N-1
    - Consider split $t_i = (\mathbf{v}_i + \mathbf{v}_{i+1}) / 2$
    - Compute classification error for threshold split $h_j(x) >= \mathbf{t}_i$
  - Choose the $\mathbf{t}^*$ with the lowest classification error

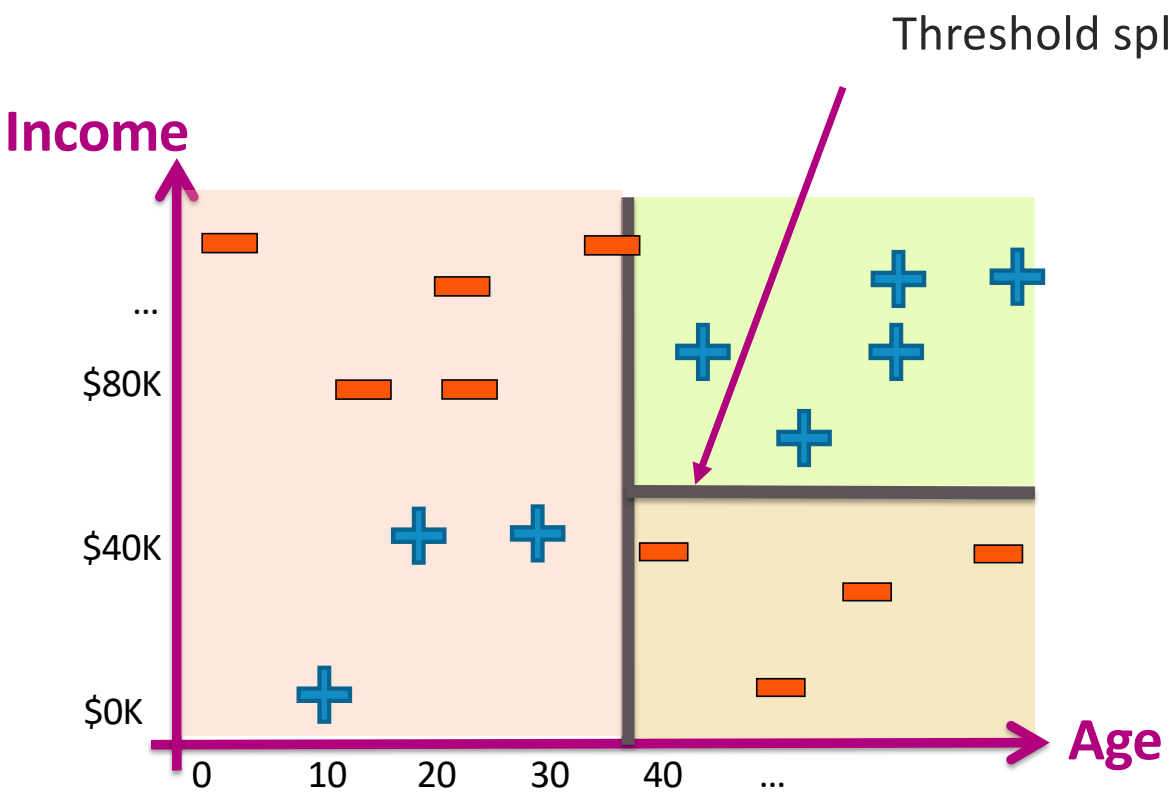
Visualizing the threshold split



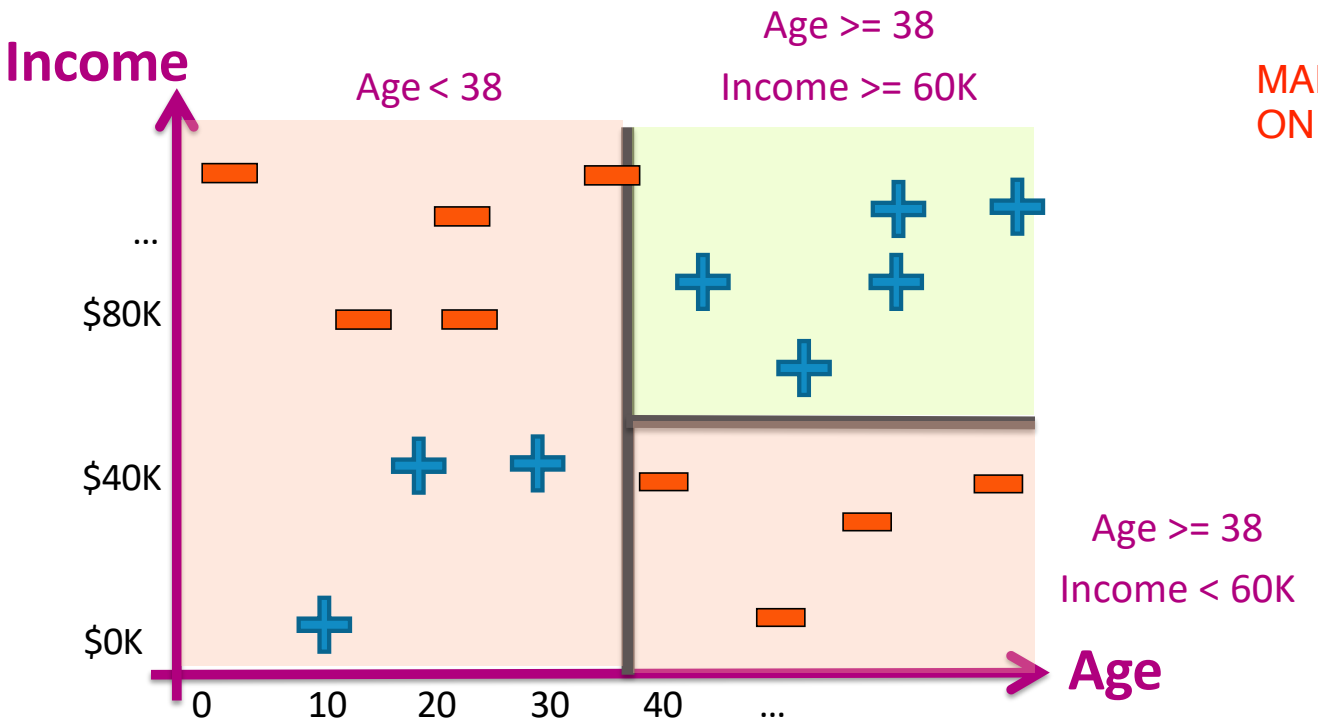
Split on Age >= 38



Depth 2: Split on Income >= $60K



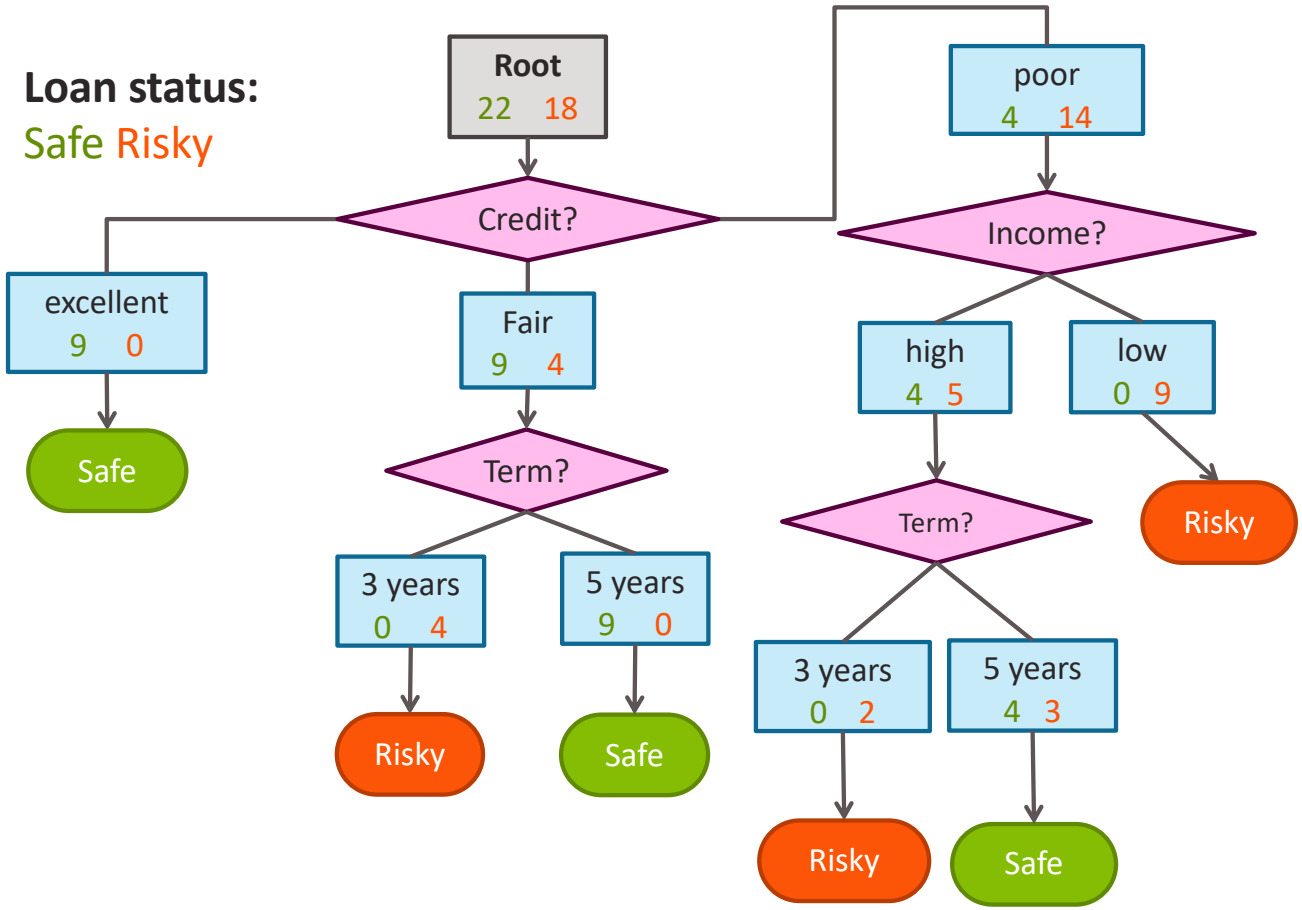
Each split partitions the 2-D space



MANY SPLIT MULTIPLE TIMES ON THE SAME FEATURE

Overfitting in decision trees

Decision tree recap

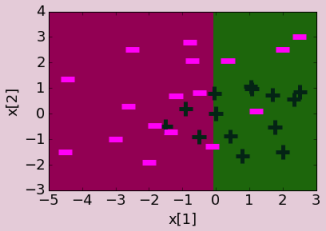
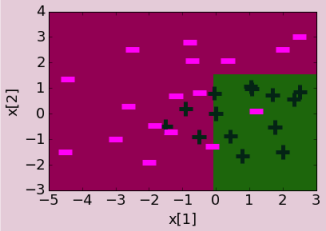
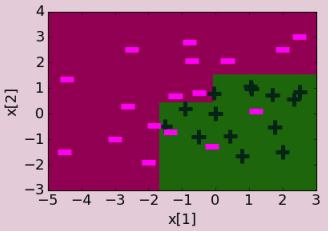
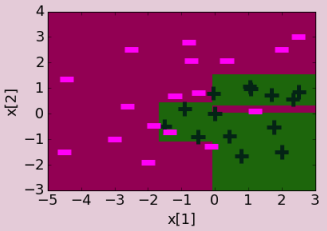
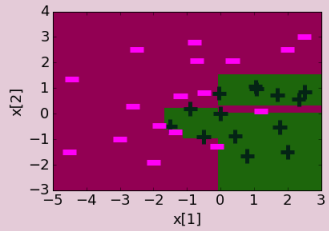


For each leaf node, set
$\hat{y}$ = majority value

What happens when we increase depth?

Training error can be set to zero if we split enough (with real valued inputs)

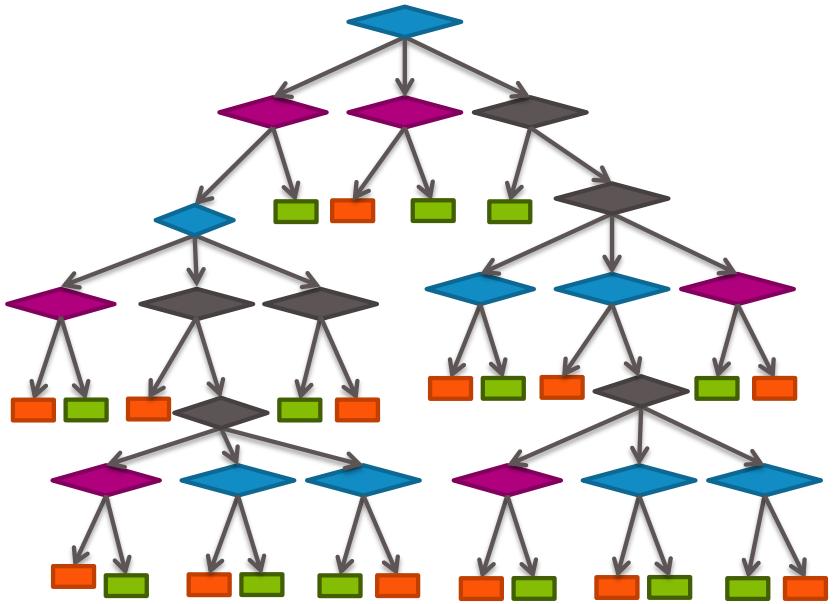
Training error reduces with depth

Tree depth	depth = 1	depth = 2	depth = 3	depth = 5	depth = 10
Training error	0.22	0.13	0.10	0.03	0.00
Decision boundary					

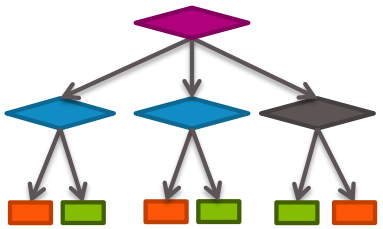
How do we regularize? In this context, simplicity

Want simple trees.

Complex Tree



Simpler Tree



Two approaches to picking simpler trees

1. Early Stopping:
   Stop the learning algorithm before tree becomes too complex

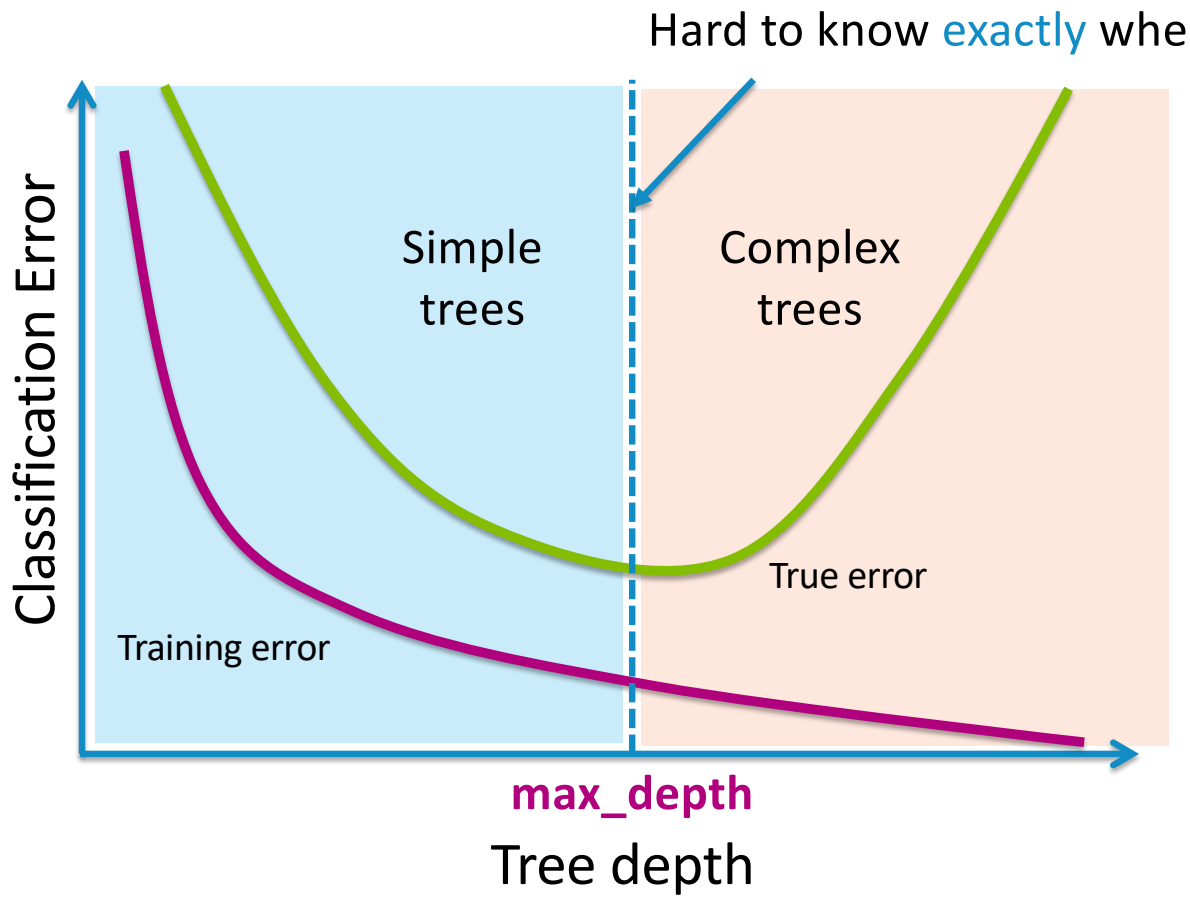
2. Pruning:
   Simplify the tree after the learning algorithm terminates

Technique 1: Early stopping

- Stopping conditions (recap):
  1. All examples have the same target value
  2. No more features to split on

- Early stopping conditions:
  1. Limit tree depth (choose *max_depth* using validation set)
  2. Do not consider splits that do not cause a sufficient decrease in classification error
  3. Do not split an intermediate node which contains too few data points

Challenge with early stopping condition 1



Also, might want some branches of tree to go deeper while others remain shallow

Early stopping condition 2: Pros and Cons

- Pros:
  - A reasonable heuristic for early stopping to avoid useless splits

- Cons:
  - Too short sighted: We may miss out on "good" splits may occur right after "useless" splits
  - Saw this with "xor" example

Two approaches to picking simpler trees

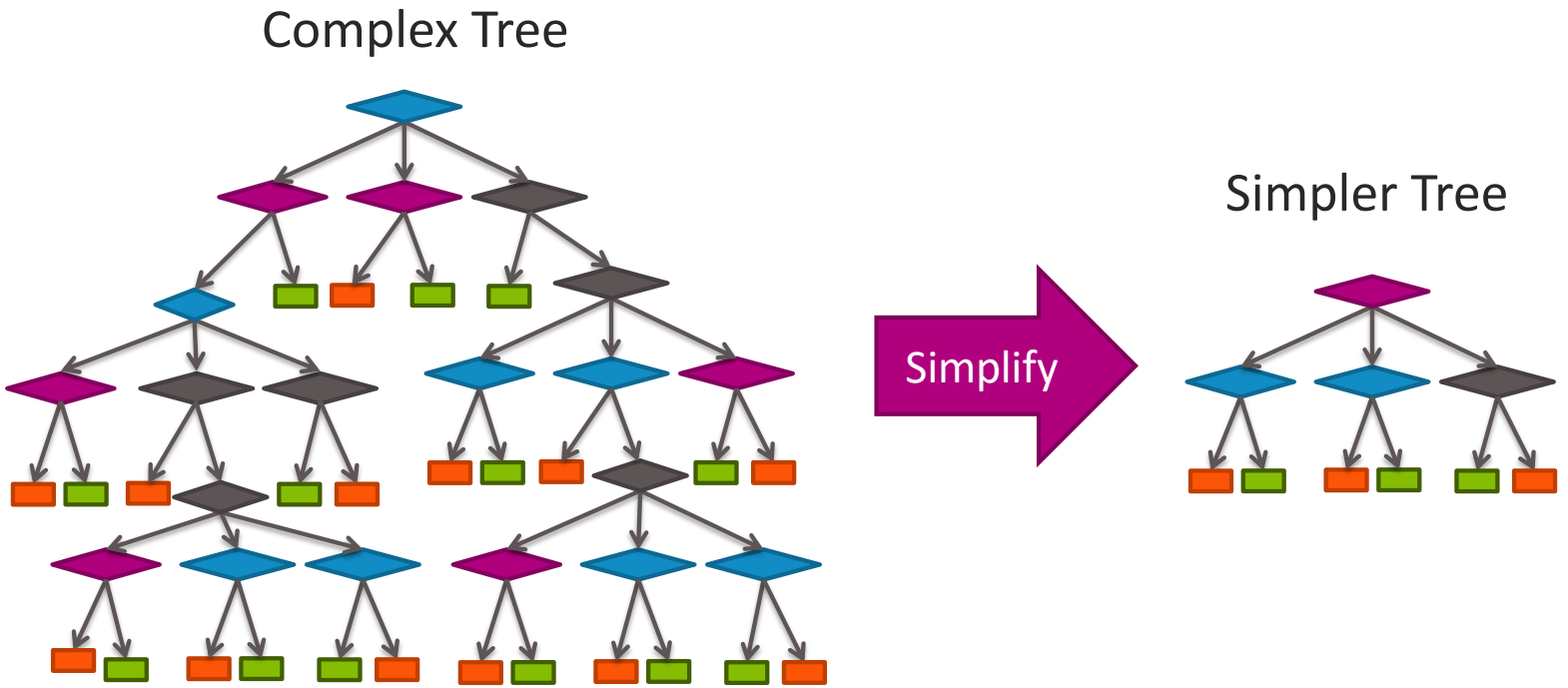
1. Early Stopping:
   Stop the learning algorithm before tree becomes too complex

2. Pruning:
   Simplify the tree after the learning algorithm terminates

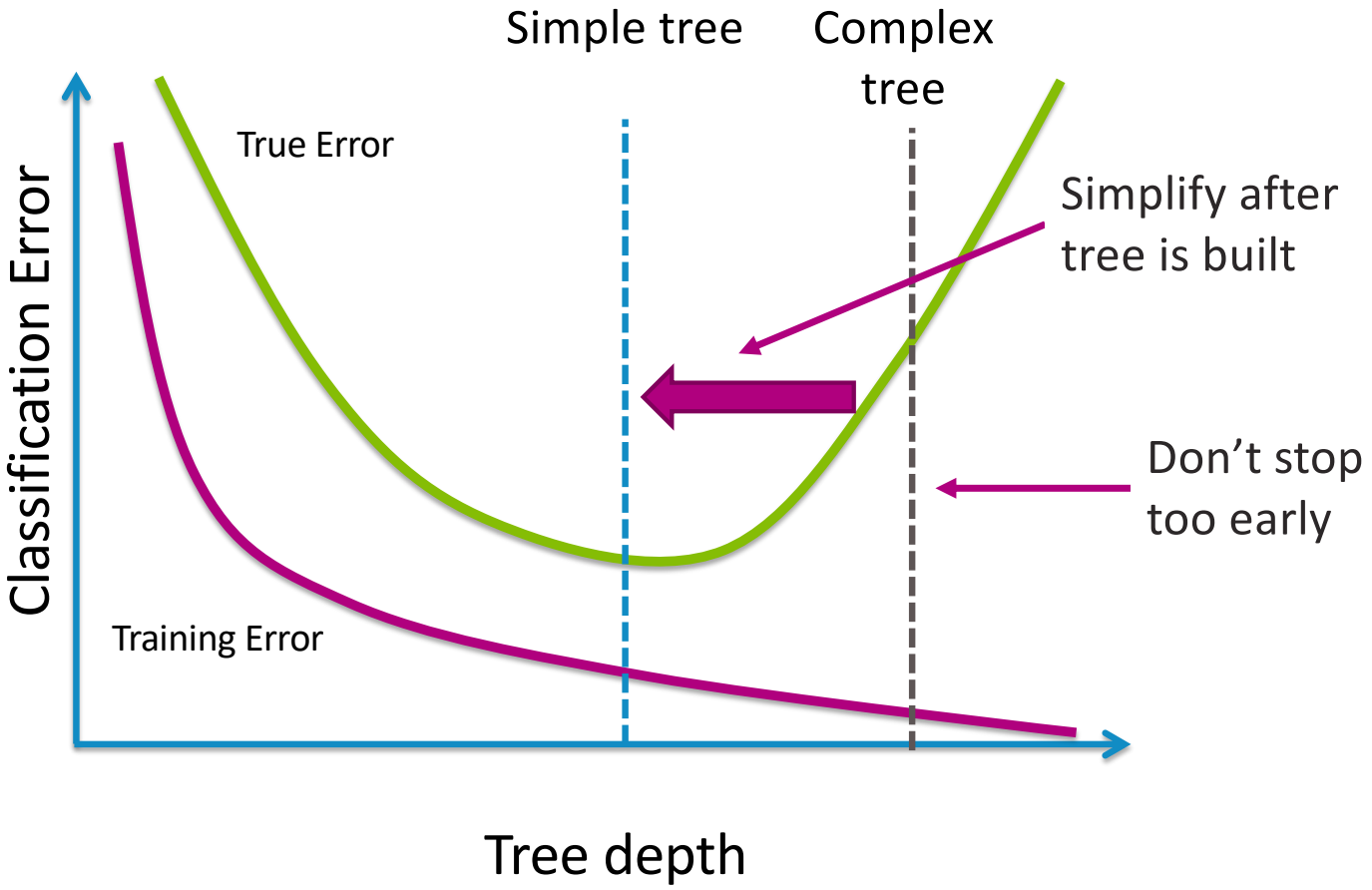
Complements early stopping

Pruning: *Intuition*

Train a complex tree, simplify later



Pruning motivation

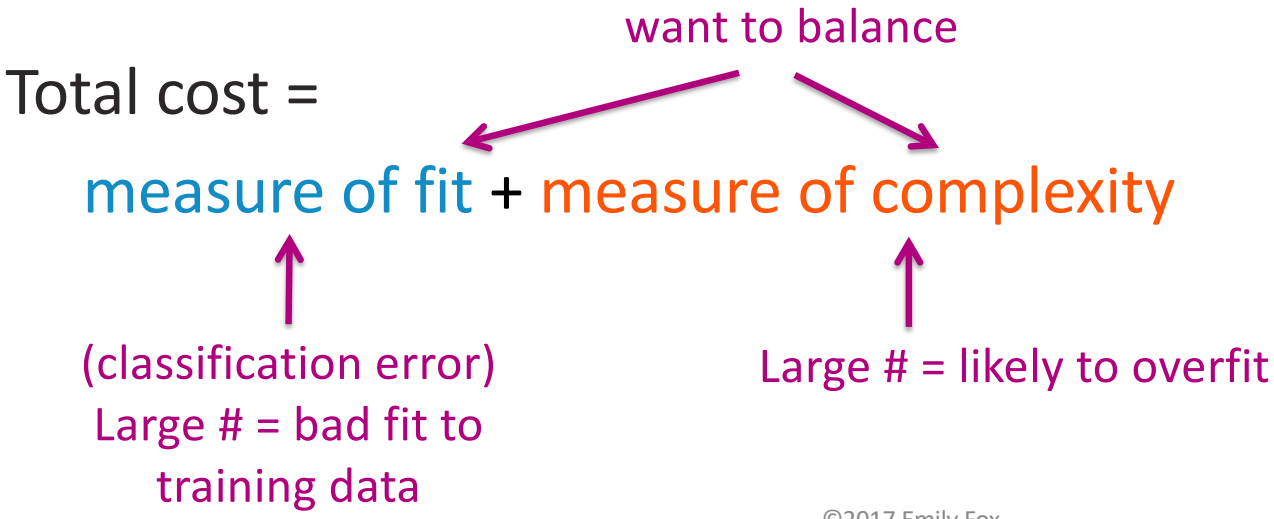


Scoring trees: Desired total quality format

Want to balance:

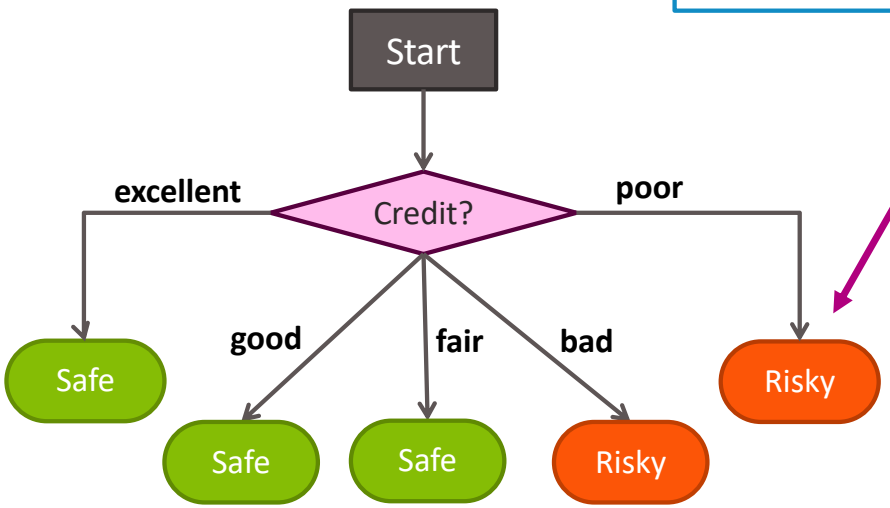
i. How well tree fits data

ii. Complexity of tree



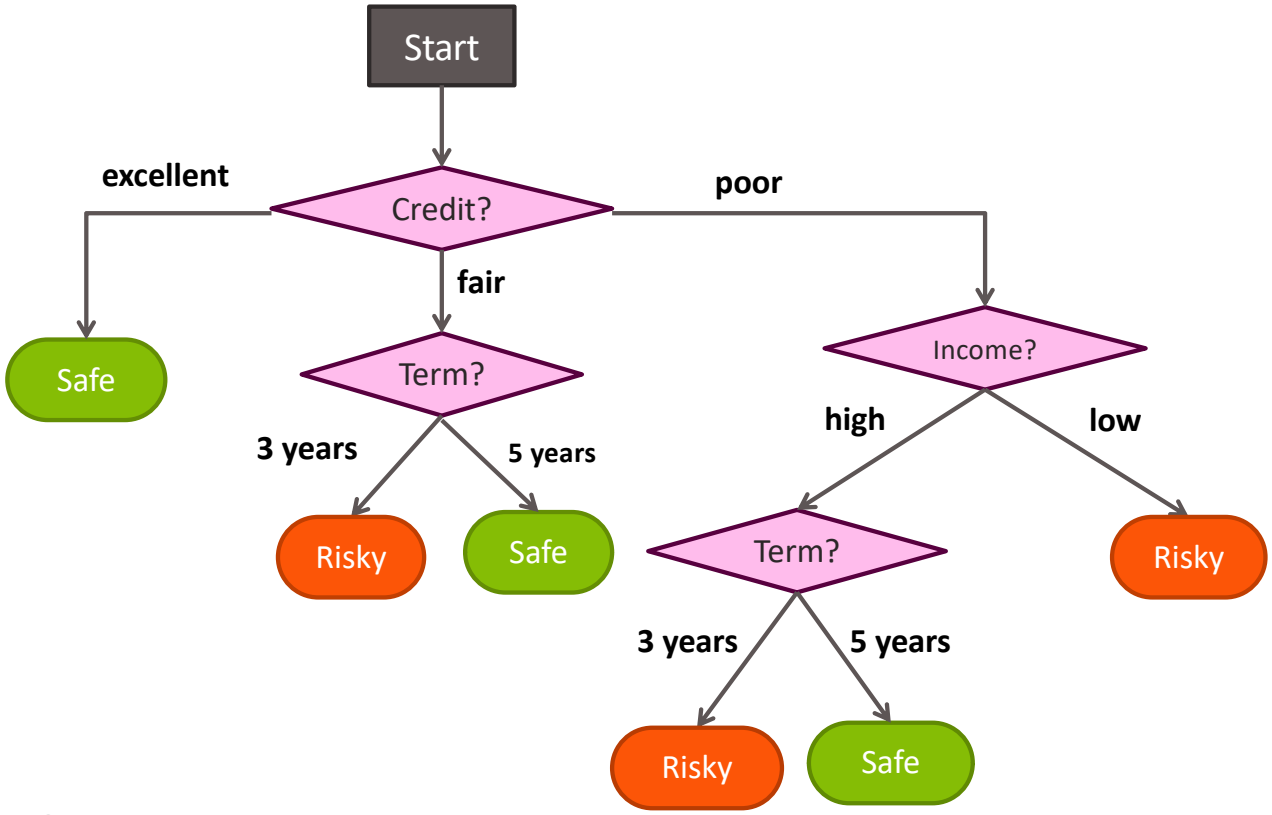
Simple measure of complexity of tree

L(T) = # of leaf nodes

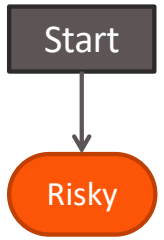


Balance simplicity & predictive power

Too complex, risk of overfitting



Too simple, high classification error



Balancing fit and complexity

$$\text{Total cost } C(T) = \text{Error}(T) + \lambda\, L(T)$$

tuning parameter

If λ=0: build out full tree.

If λ=∞: won't ever split.

If λ in between:

Having said all that…

Vanilla decision trees just don't really work very well.

Bagging

Bootstrap aggregation!

CSE 446: Machine Learning

Suppose we want to reduce variance

Recall definition of variance $\mathbb{E}\left[(f_D(x) - \mathbb{E}_D[f_D(x)])^2\right]$

If we had lots of **independent** data sets, we could average their results and get the variance to approach 0

Given m independent data sets (D_1, …, D_m), each of size n,
learn m classifiers (f_1, …, f_m), where f_i trained on D_i.

By law of large numbers $\frac{1}{m}\sum_i f_{D_i}(x) \rightarrow \mathbb{E}_D(f_D(x))$.

But we don't have lots of data sets

BOOTSTRAP!

Bootstrap Aggregation (aka bagging)

- A technique for addressing high variance (e.g. in decision trees)
  - Given sample D, draw m samples (D_1, …, D_m) of size n, with replacement.
  - Train a classifier on each.
  - Use average (for regression) or majority vote (for classification).

Advantages of bagging

- Easy to implement
- Reduces variance
- Gives information about uncertainty of prediction.
- Provides estimate of test error, "out of bag" error without using validation set.

Let $S_i = \{k \mid (\mathbf{x}_i, y_i) \notin D_k\}$ and define $\tilde{f}_i(\mathbf{x}) = \frac{1}{|S_i|} \sum_{k \in S_i} f_k(\mathbf{x}_i)$

all datapoints you left out; the ones that were not drawn as part of random bootstrap sample of the current dataset

Then out of bag error is: $\frac{1}{n} \sum_{(\mathbf{x}_i, y_i) \in D} \ell(\tilde{f}_i(\mathbf{x}_i), h_i)$

Bagging produces an ensemble classifier

Ensemble classifier in general

- Goal:
  - Predict output y
    - Either +1 or -1
  - From input x
- Learn ensemble model:
  - Classifiers: $f_1(x), f_2(x), \ldots, f_T(x)$
  - Coefficients: $\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_T$
- Prediction:

$$\hat{y} = sign\left(\sum_{t=1}^{T} \hat{\mathbf{w}}_t f_t(\mathbf{x})\right)$$

Random Forests

CSE 446: Machine Learning

One of the most useful bagged algorithms

- Given data set D, draw m samples (D_1, …, D_m) of size n from D, with replacement.
- For each D_j, train a full decision tree h_j with one **crucial modification:**
  - *Before each split, randomly subsample k features (without replacement) and only consider these for your split.*
- Final classifier obtained by averaging.

One of best, most popular and easiest to use algorithms

number bootstrap samples

number of features to subsample

- Only two hyperparameters m and k.
- Extremely insensitive to both.
  - Classification: good choice for k is $\sqrt{d}$ (where d is number of features)
  - Regression: good choice for k is d/3
  - Set m as large as you can afford.
- Works really well!
- Features can be of different scale, magnitude, etc.
  - Very convenient with heterogeneous features.

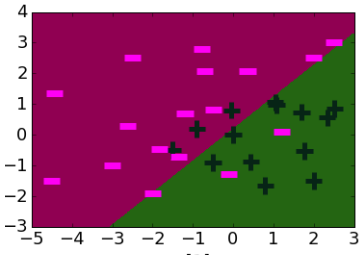
Boosting

CSE 446: Machine Learning

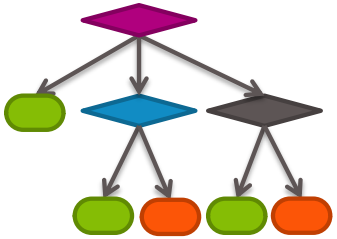
Emily Fox
University of Washington

January 30, 2017

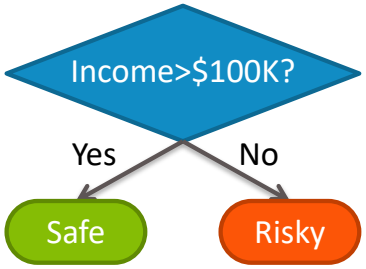
Simple (weak) classifiers are good!



Logistic regression w. simple features



Shallow decision trees

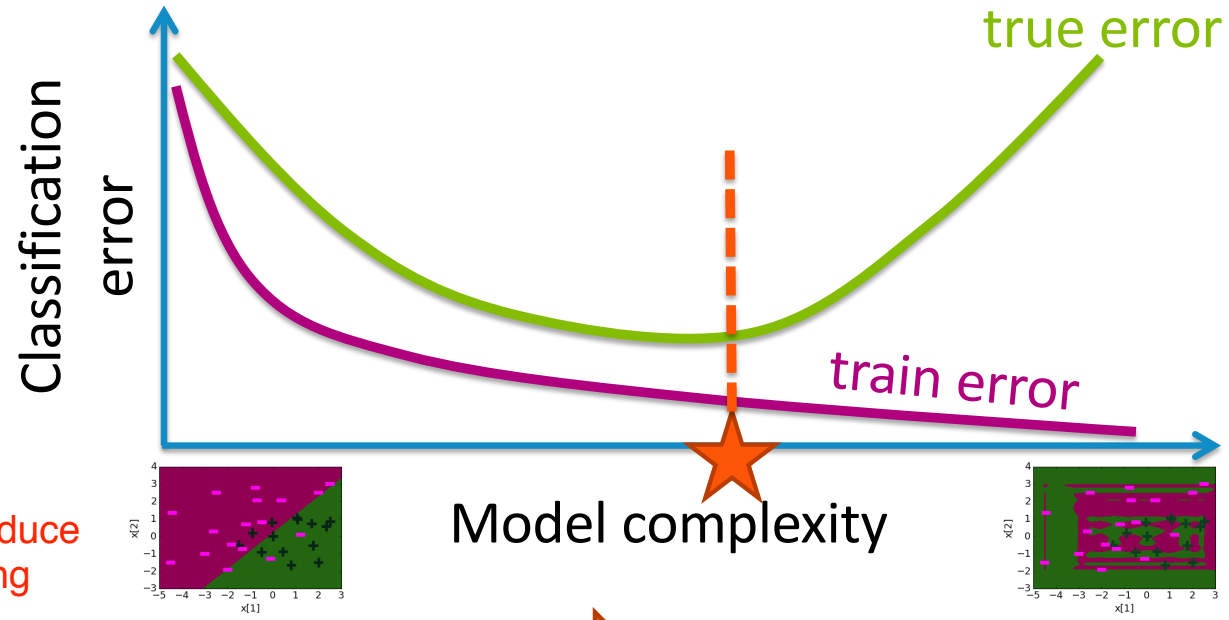


Decision stumps

Low variance. Learning is fast!

But high bias…

Finding a classifier that's just right

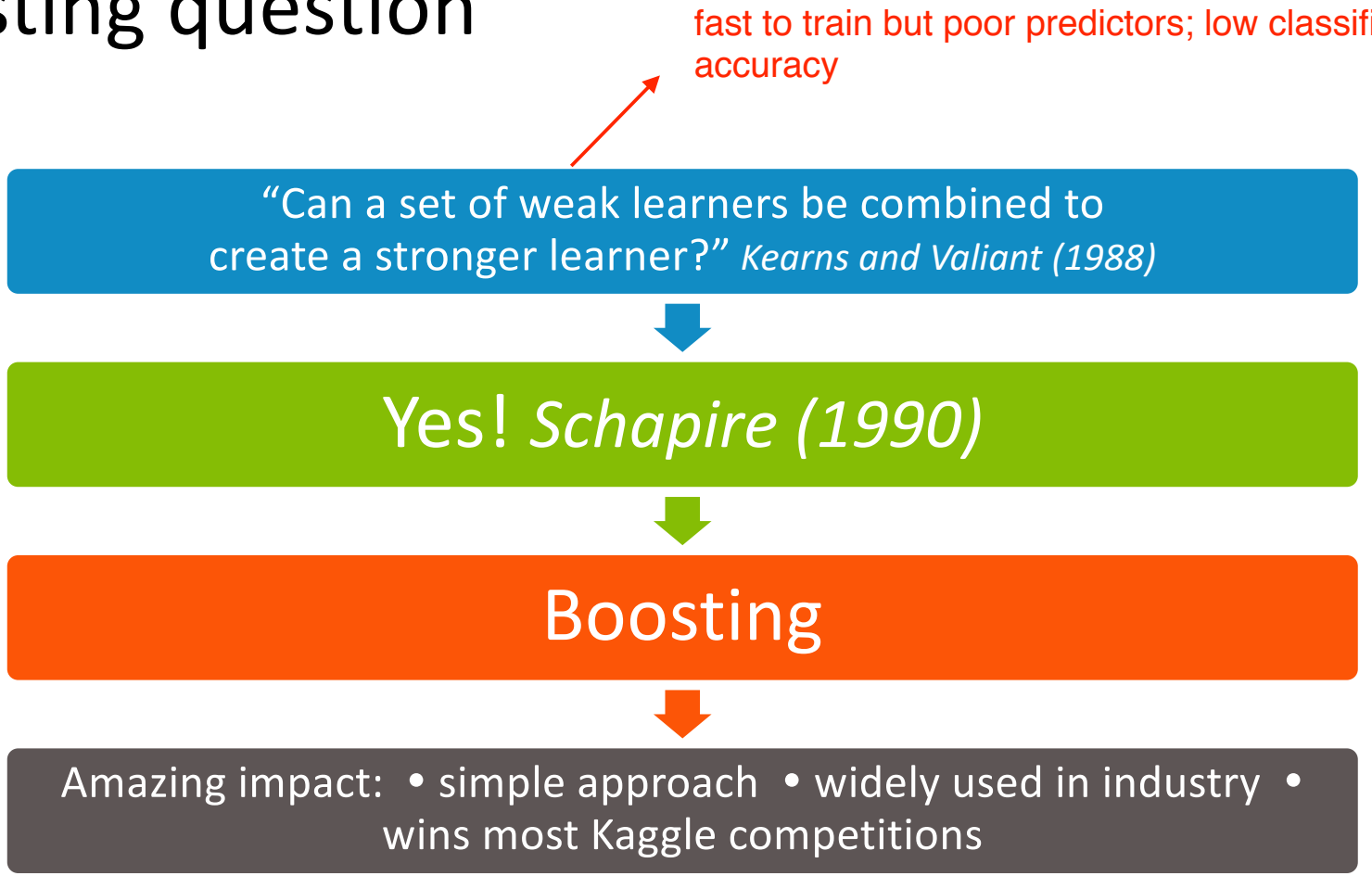


Don't produce very strong results

Weak learner → Need stronger learner

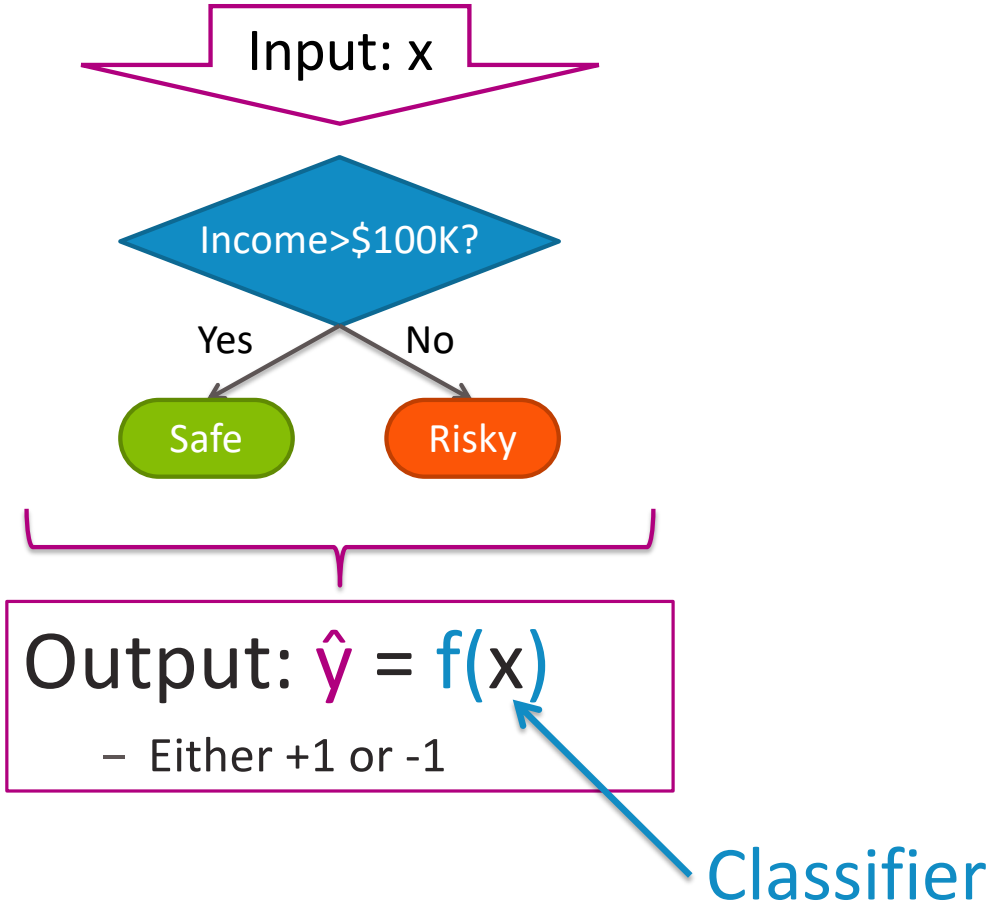
Option 1: add more features or depth
Option 2: ?????

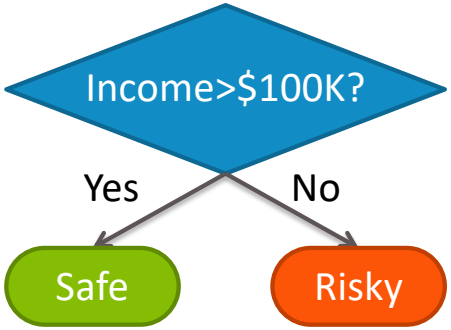
Boosting question



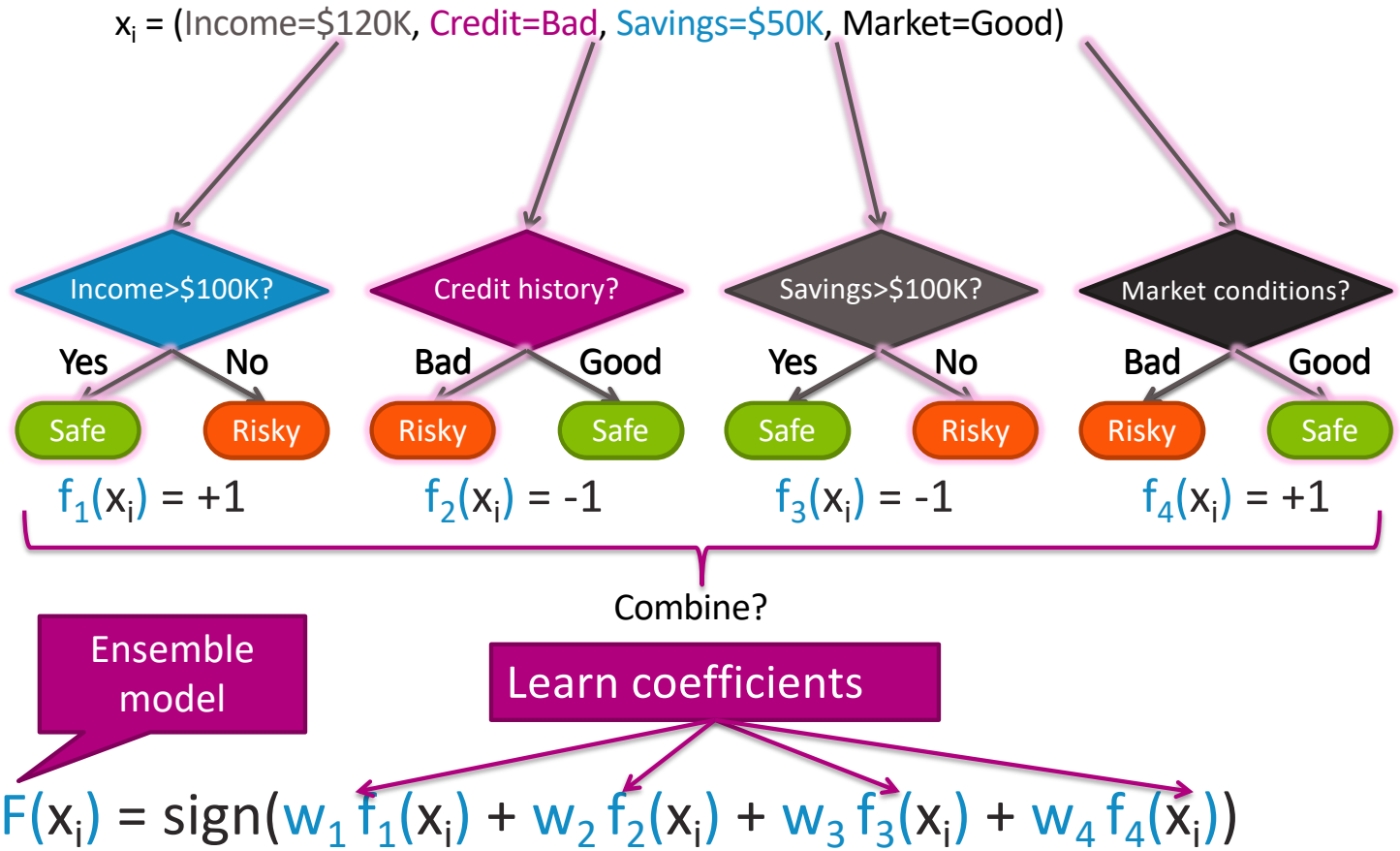
Ensemble classifier

A single classifier





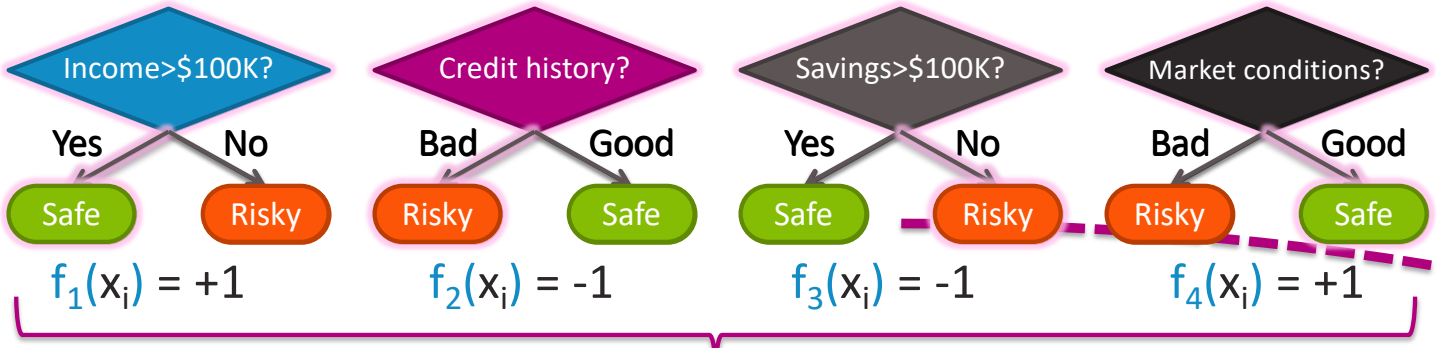
Ensemble methods: Each classifier "votes" on prediction



combine weak models…

Boosting = learning which weak learners to use and how to weight the outputs of each of them

Prediction with ensemble



Combine?

Ensemble model

Learn coefficients

$$F(x_i) = \text{sign}(w_1 f_1(x_i) + w_2 f_2(x_i) + w_3 f_3(x_i) + w_4 f_4(x_i))$$

w_1	2
w_2	1.5
w_3	1.5
w_4	0.5

Ensemble classifier in general

- Goal:
  - Predict output y
    - Either +1 or -1
  - From input x
- Learn ensemble model:
  - Classifiers: $f_1(x), f_2(x), \ldots, f_T(x)$
  - Coefficients: $\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_T$
- Prediction:

$$\hat{y} = sign\left(\sum_{t=1}^{T} \hat{\mathbf{w}}_t f_t(\mathbf{x})\right)$$

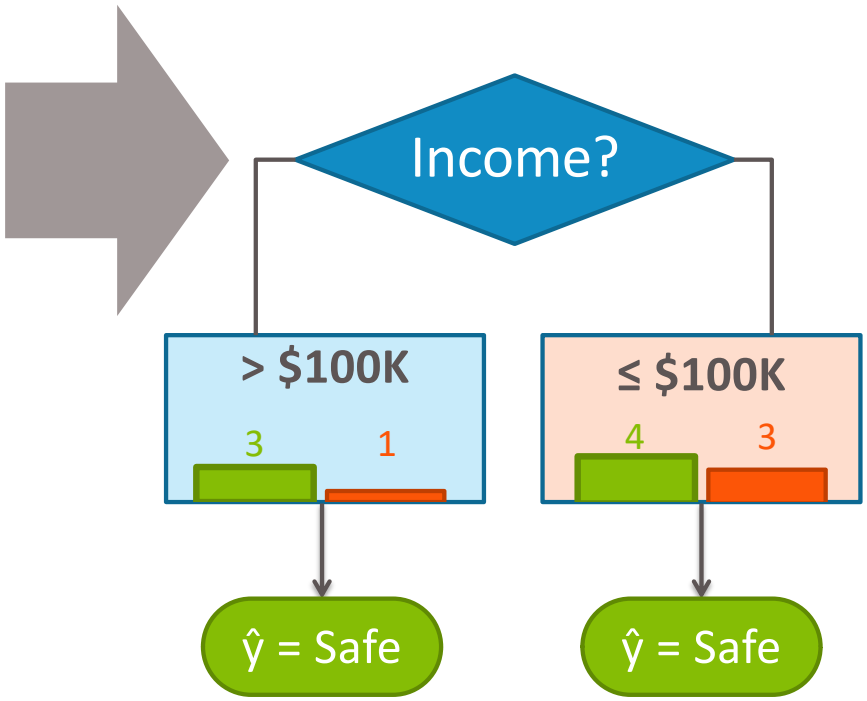
Boosting

Training a classifier

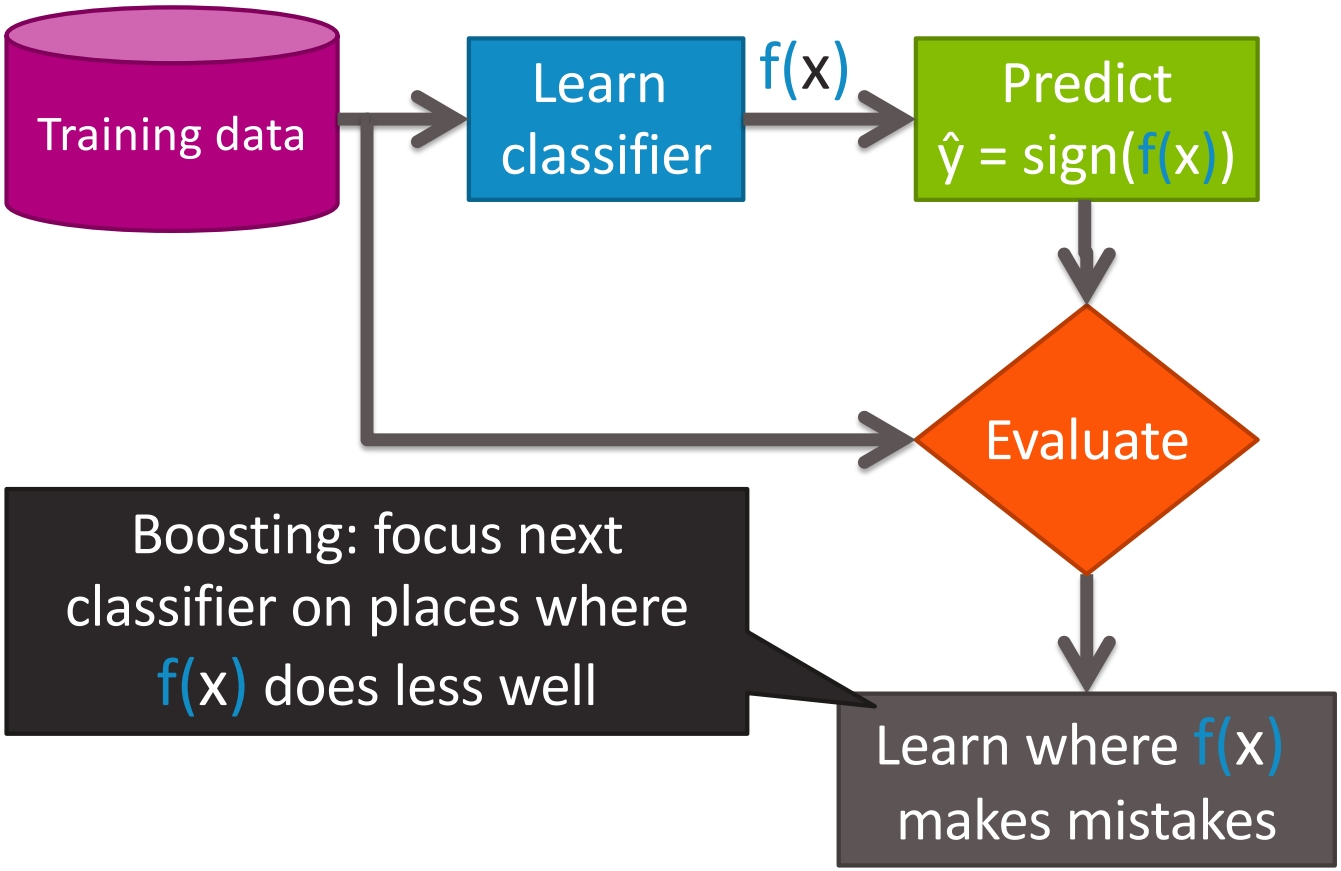
Learning decision stump

just a single split…

	Credit	Income	y
	A	$130K	Safe
X	B	$80K	Risky
X	C	$110K	Risky
	A	$110K	Safe
	A	$90K	Safe
	B	$120K	Safe
X	C	$30K	Risky
X	C	$60K	Risky
	B	$95K	Safe
	A	$60K	Safe
	A	$98K	Safe



Boosting = Focus learning on "hard" points



Learning on weighted data:

More weight on "hard" or more important points

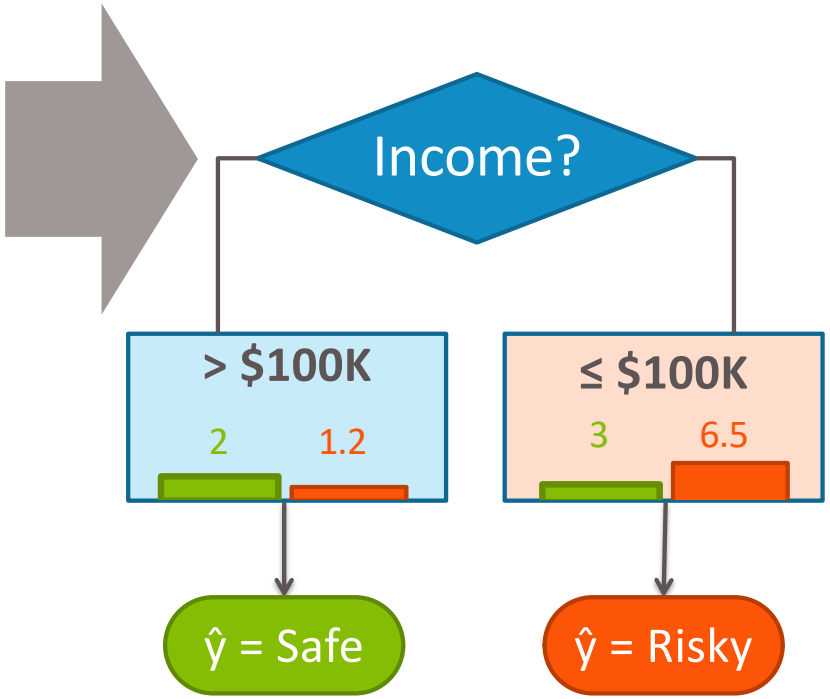
- Weighted dataset:
  - Each x_i, y_i weighted by α_i
    - More important point = higher weight α_i

- Learning:
  - Data point i counts as α_i data points
    - E.g., $\alpha_i = 2$ ➔ count point twice

Learning a decision stump on weighted data

Increase weight α of harder/misclassified points

	Credit	Income	y	Weight α
	A	$130K	Safe	0.5
X	B	$80K	Risky	1.5
X	C	$110K	Risky	1.2
	A	$110K	Safe	0.8
	A	$90K	Safe	0.6
	B	$120K	Safe	0.7
X	C	$30K	Risky	3
X	C	$60K	Risky	2
	B	$95K	Safe	0.8
	A	$60K	Safe	0.7
	A	$98K	Safe	0.9

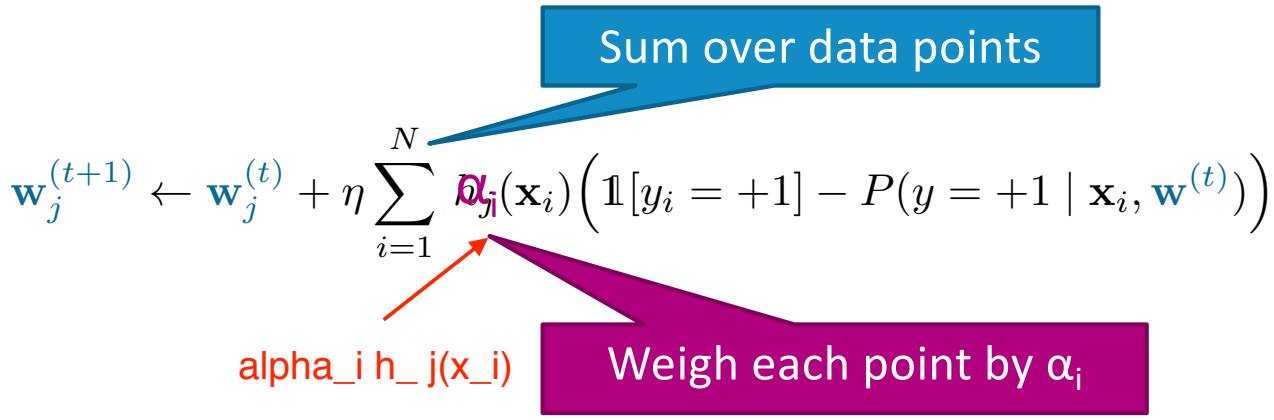


alpha > 1 in places where we made an error and < 1 in places (datapoints) where we did not make an error

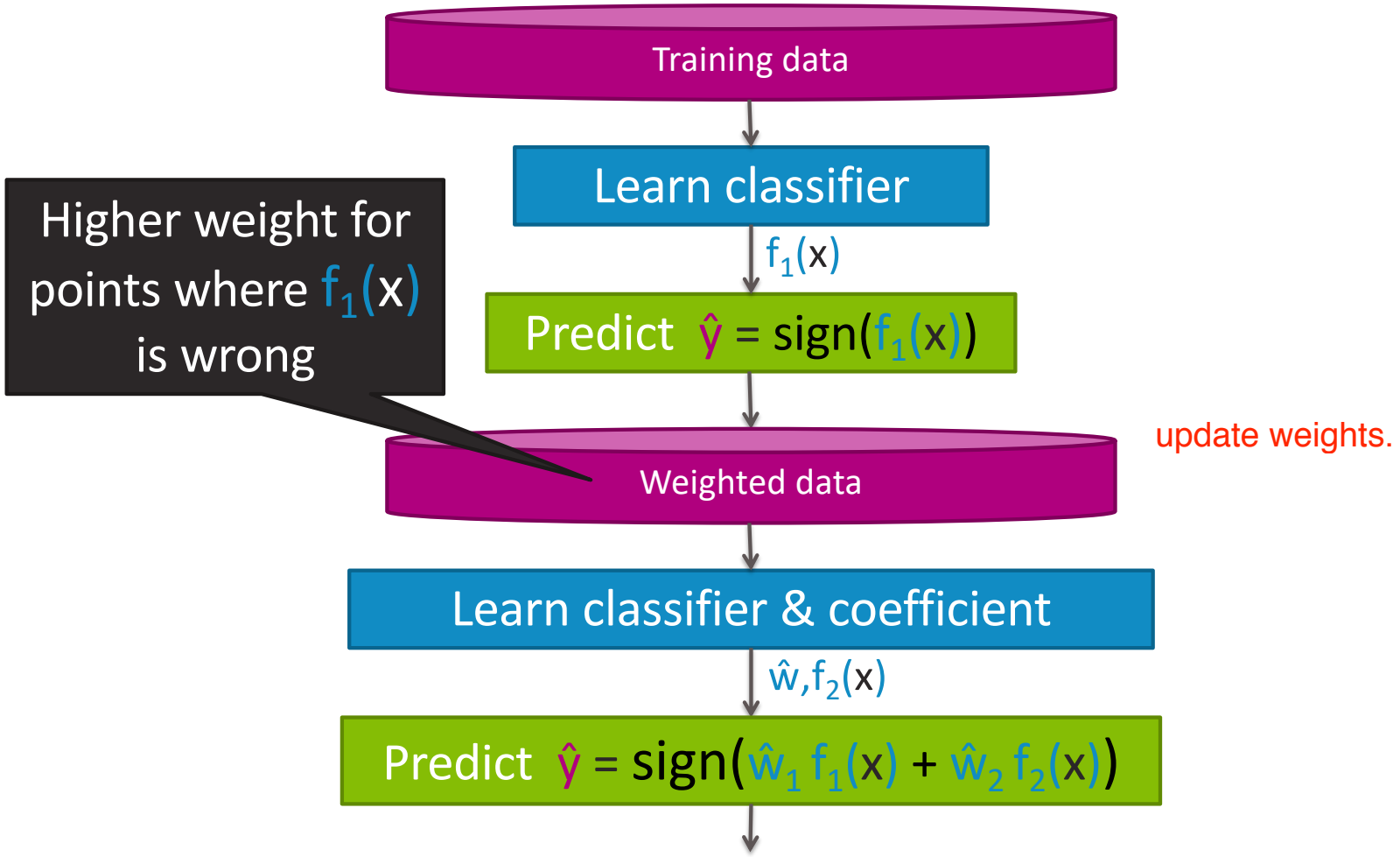
Learning from weighted data in general

- Learning from weighted data generally no harder.
  - Data point i counts as α_i data points

- E.g., gradient descent for logistic regression:



Boosting = Greedy learning ensembles from data



AdaBoost

AdaBoost: learning ensemble

[Freund & Schapire 1999]

- Start with same weight for all points: $\alpha_i = 1/N$

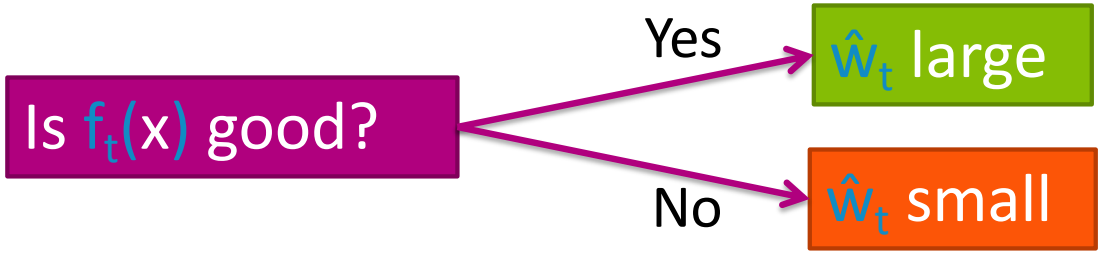
- For t = 1,…,T
  - Learn $f_t(x)$ with data weights α_i
  - Compute coefficient $\hat{w}_t$
  - Recompute weights α_i

- Final model predicts by:

$$\hat{y} = sign\left(\sum_{t=1}^{T} \hat{\mathbf{w}}_t f_t(\mathbf{x})\right)$$

Computing coefficient $\hat{w}_t$

AdaBoost: Computing coefficient $\hat{w}_t$ of classifier $f_t(x)$



- $f_t(x)$ is good ➔ f_t has low training error

- Measuring error in weighted data?
  - Just weighted # of misclassified points

Weighted classification error

Learned classifier

$\hat{y}$ =

Data point

(Sushi was great, α=0.5)

Mistake!

Weight of correct	1.2
Weight of mistakes	0.5

Hide label

Weighted classification error

- Total weight of mistakes: $\sum_i \alpha_i \mathbb{1}(\hat{y}_i \neq y_i)$ sum of alphas over all datapoints where you make an error
- Total weight of all points: $\sum_{i=1}^{n} \alpha_i$ sum of alpha
- Weighted error measures fraction of weight of mistakes:

$$\text{weighted\_error} = \frac{\text{Total weight of all mistakes}}{\text{Total weight of all data}}$$

  - Best possible value is 0.0

Worst possible value is 1.0

Actual worst is 0.5

DONT NEED FOR FINAL

AdaBoost: updating weights

Formula for computing coefficient $\hat{w}_t$ of classifier $f_t(x)$

$$\hat{\mathbf{w}}_t = \frac{1}{2} \ln \left(\frac{1 - weighted\_error(f_t)}{weighted\_error(f_t)} \right)$$

Is $f_t(x)$ good?

Yes

No

weighted_error(f_t) on training data	$\frac{1 - weighted\_error(f_t)}{weighted\_error(f_t)}$	$\hat{w}_t$
0.01	(1-0.01)/0.01 = 99	0.5 ln(99) = 2.3
0.5	(1-0.5)/0.5 = 1	0.5 ln(1) = 0
0.99	(1-0.99)/0.99 = 0.01	0.5 ln(0.01) = -2.3

Last one is a terrible classifier, but - $f_t(x)$ is great!

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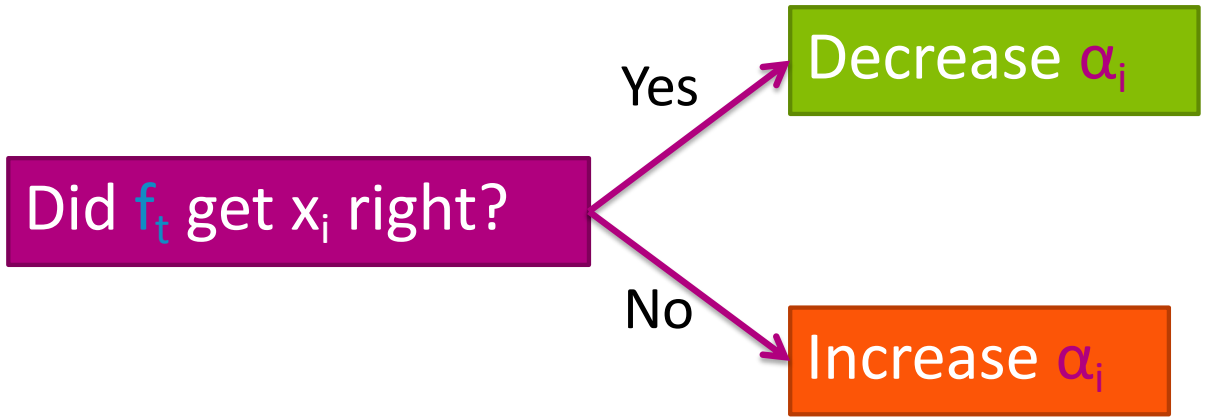
- Final model predicts by:

$$\hat{y} = sign\left(\sum_{t=1}^{T} \hat{\mathbf{w}}_t f_t(\mathbf{x}) \right)$$

Recompute weights α_i

AdaBoost: Updating weights α_i based on where classifier $f_t(x)$ makes mistakes



AdaBoost: Formula for updating weights α_i

$$\alpha_i \leftarrow \begin{cases} \alpha_i e^{-\hat{w}_t}, & \text{if } f_t(x_i)=y_i \\ \alpha_i e^{\hat{w}_t}, & \text{if } f_t(x_i)\neq y_i \end{cases}$$

Did f_t get x_i right?

Yes / No

$f_t(x_i)=y_i$?	$\hat{w}_t$	Multiply α_i by	Implication
correct	2.3	$e^{-2.3} = 0.1$	Decrease importance of x_i, y_i
correct	0	$e^{-0} = 1$	Keep importance same
mistake	2.3	$e^{2.3} = 9.98$	Increase importance
mistake	0	$e^{-0} = 1$	Keep importance same

AdaBoost: learning ensemble

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$$\hat{\mathbf{w}}_t = \frac{1}{2}\ln\left(\frac{1 - weighted\_error(f_t)}{weighted\_error(f_t)}\right)$$

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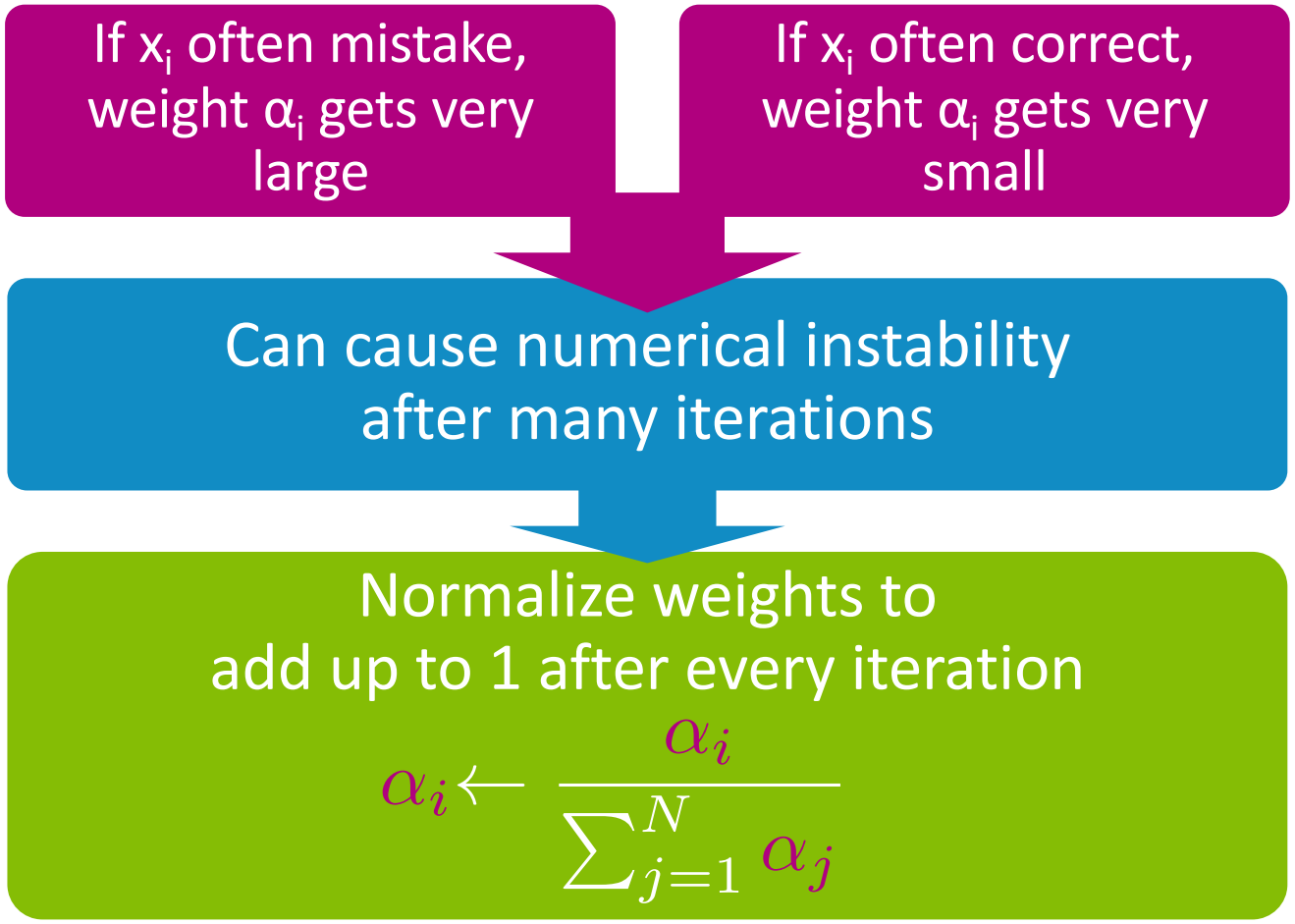
- Final model predicts by:

$$\hat{y} = sign\left(\sum_{t=1}^{T} \hat{\mathbf{w}}_t f_t(\mathbf{x})\right)$$

AdaBoost: Normalizing weights α_i



AdaBoost: learning ensemble

- Start with same weight for all points: $\alpha_i = 1/N$
- For t = 1,…,T
  - Learn $f_t(x)$ with data weights α_i
  - Compute coefficient $\hat{w}_t$
  - Recompute weights α_i
  - Normalize weights α_i
- Final model predicts by:

$$\hat{y} = sign\left(\sum_{t=1}^{T} \hat{w}_t f_t(x)\right)$$

$$\hat{w}_t = \frac{1}{2}\ln\left(\frac{1 - weighted\_error(f_t)}{weighted\_error(f_t)}\right)$$

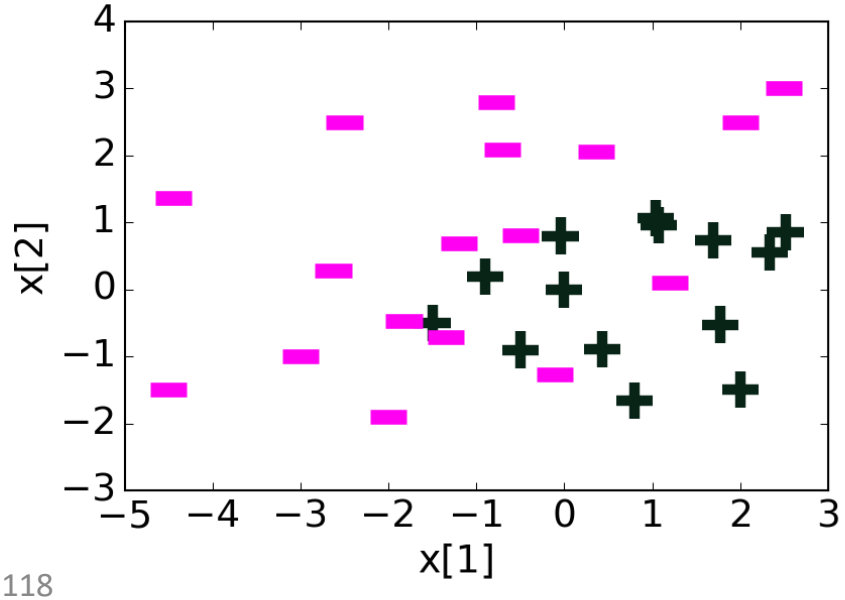
$$\alpha_i \leftarrow \begin{cases} \alpha_i e^{-\hat{w}_t}, & \text{if } f_t(x_i) = y_i \\ \alpha_i e^{\hat{w}_t}, & \text{if } f_t(x_i) \neq y_i \end{cases}$$

$$\alpha_i \leftarrow \frac{\alpha_i}{\sum_{j=1}^{N} \alpha_j}$$

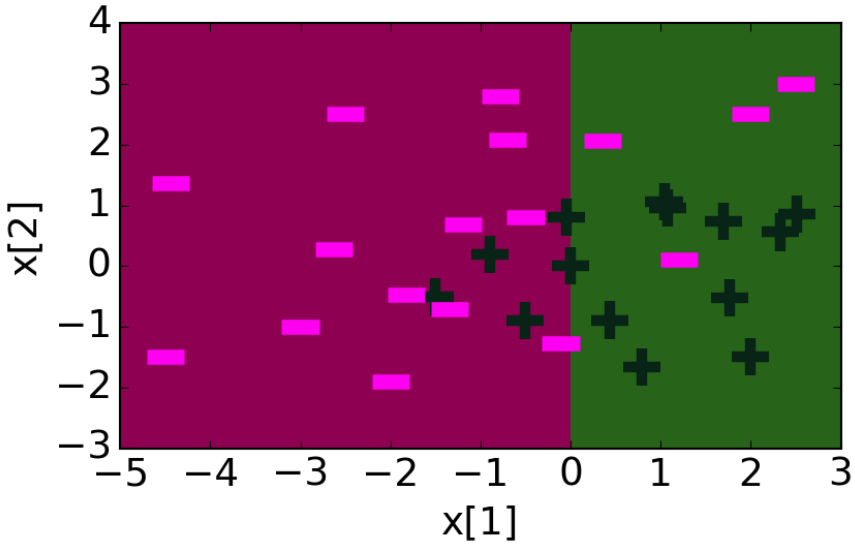
AdaBoost example

t=1: Just learn a classifier on original data

Original data



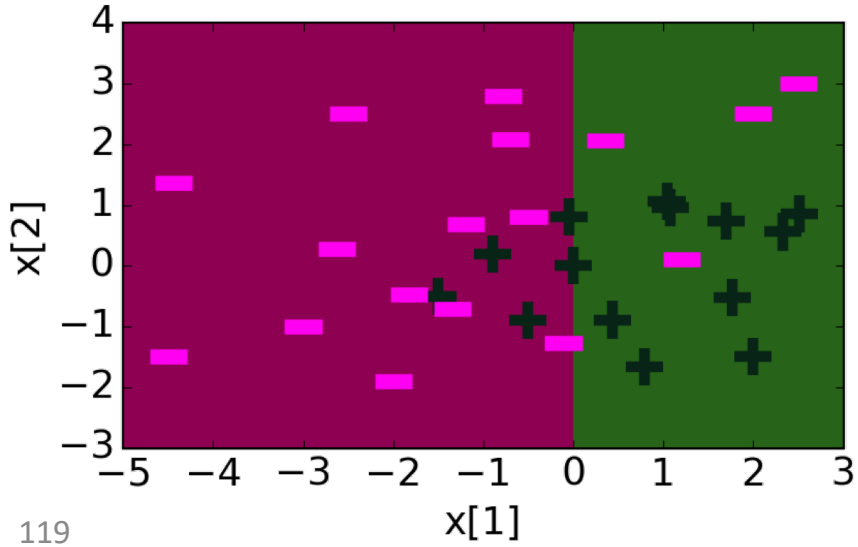
Learned decision stump $f_1(x)$



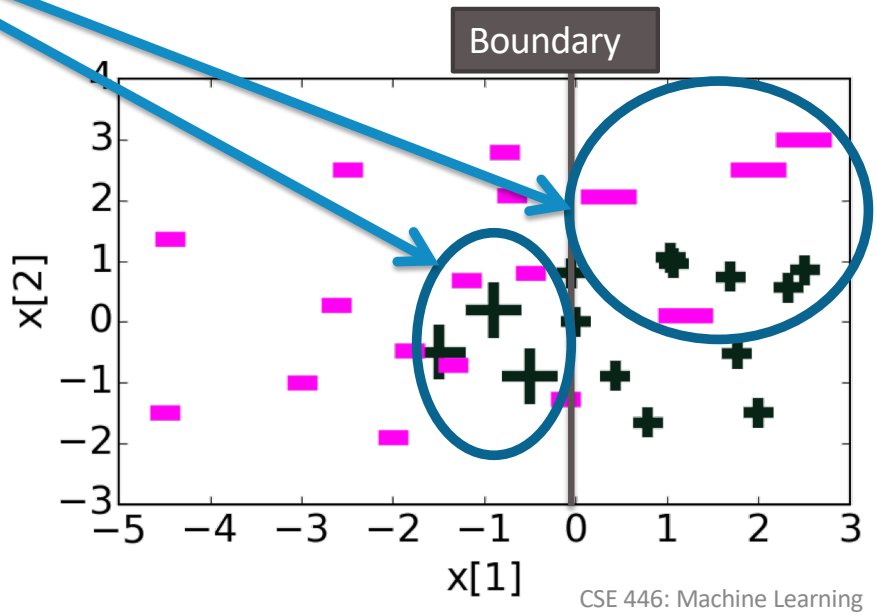
Updating weights α_i

Increase weight α_i of misclassified points

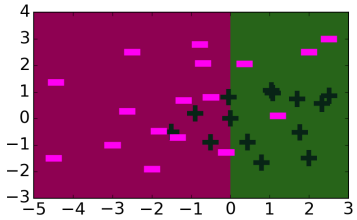
Learned decision stump $f_1(x)$



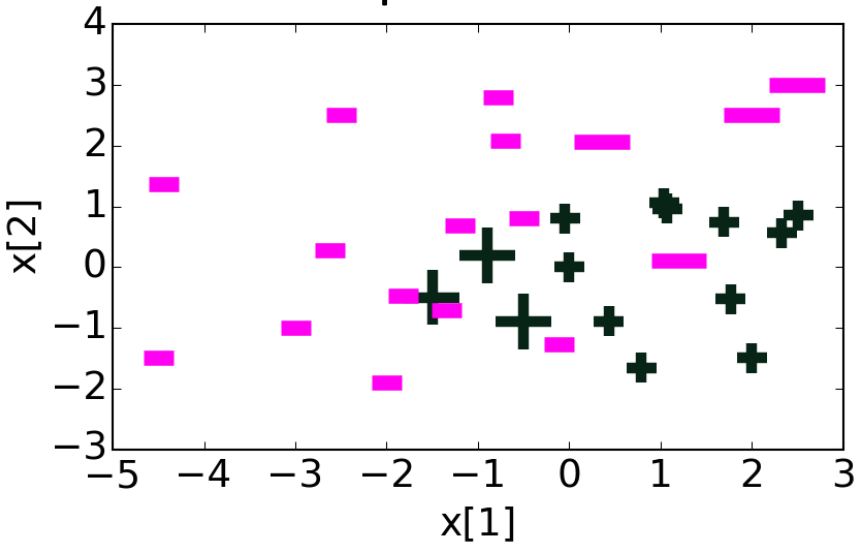
New data weights α_i



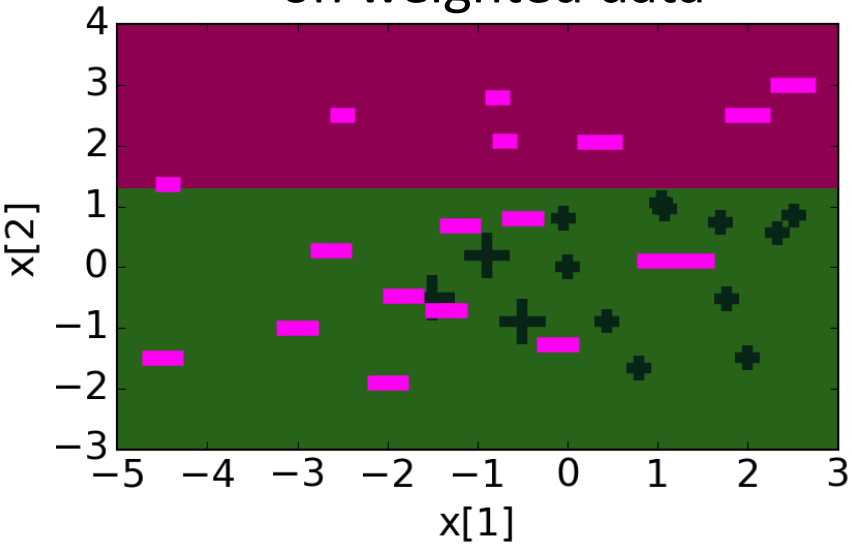
t=2: Learn classifier on weighted data

$f_1(x)$ 

Weighted data: using α_i chosen in previous iteration

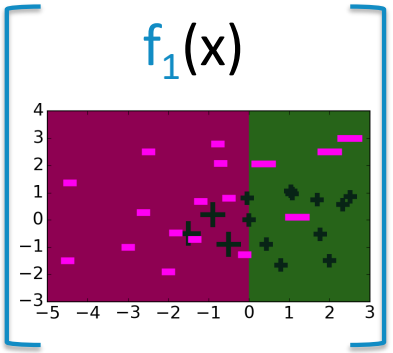
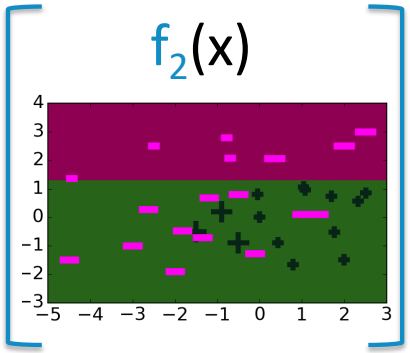
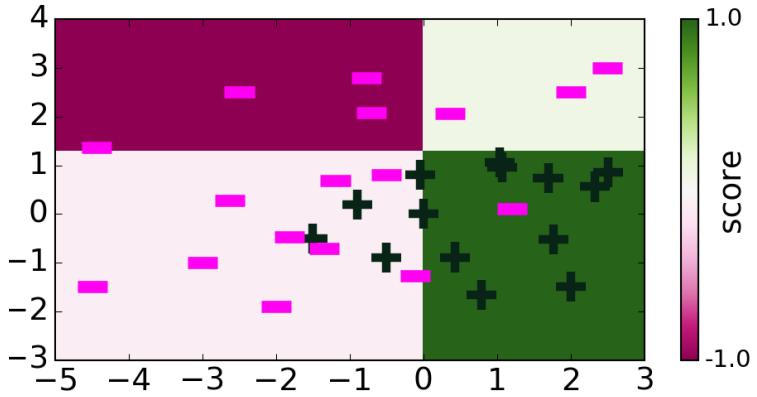


Learned decision stump $f_2(x)$ on weighted data

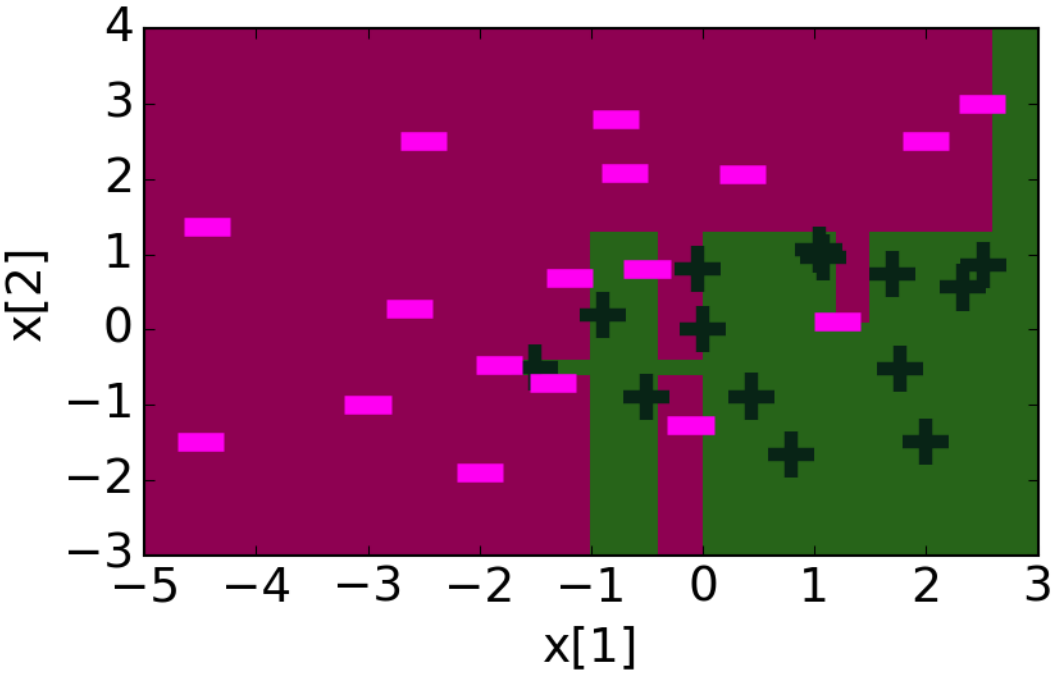


Ensemble becomes weighted sum of learned classifiers

$\hat{w}_1$ $f_1(x)$ $\hat{w}_2$ $f_2(x)$

0.61  + **0.53**  = 

Decision boundary of ensemble classifier after 30 iterations



training_error = 0

Boosting convergence & overfitting

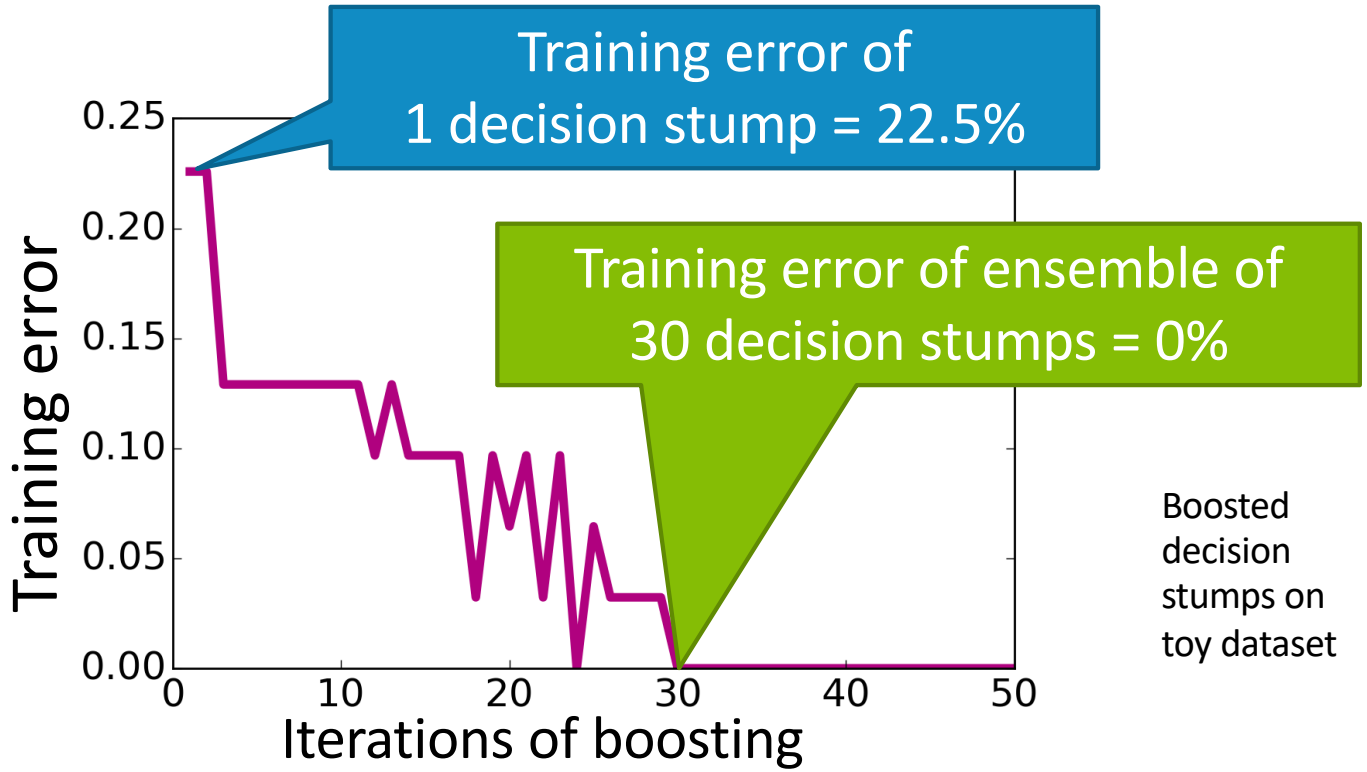
Boosting question revisited

"Can a set of weak learners be combined to create a stronger learner?" *Kearns and Valiant (1988)*

Yes! *Schapire (1990)*

Boosting

After some iterations, training error of boosting goes to zero!!!

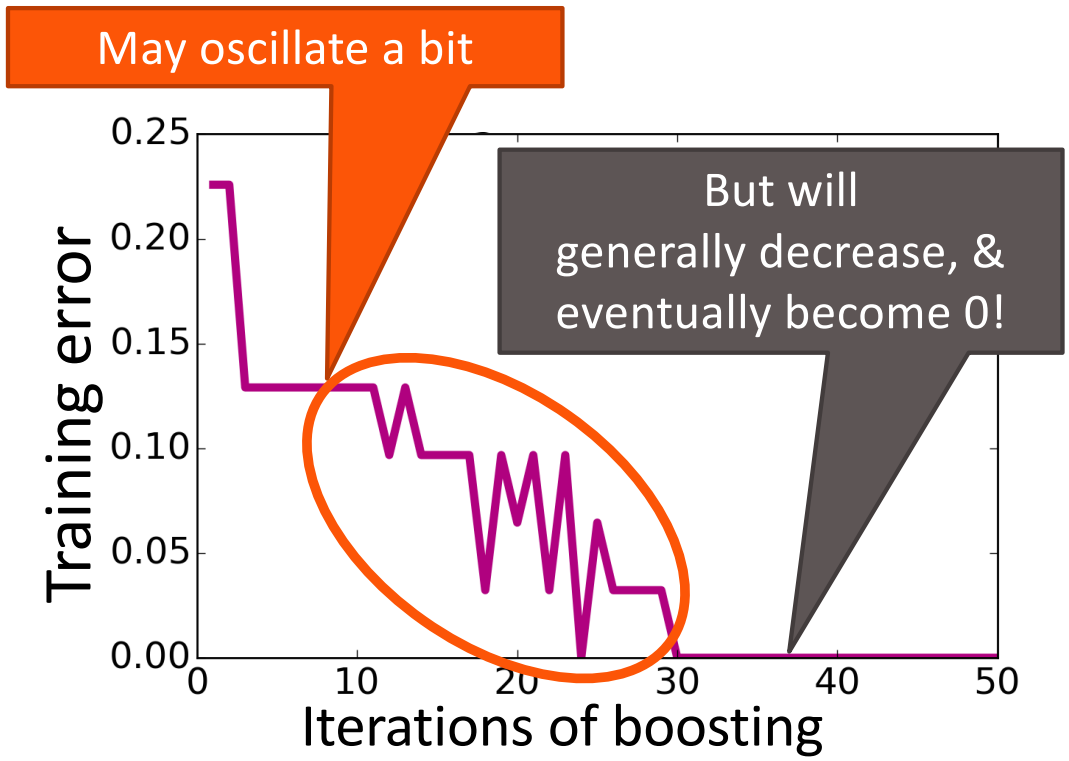


Boosted decision stumps on toy dataset

AdaBoost Theorem

Under some technical conditions…

Training error of boosted classifier → 0 as T→∞



Condition of AdaBoost Theorem

Under some technical conditions…

Training error of boosted classifier → 0 as T→∞

Condition = At every t, can find a weak learner with weighted_error(f_t) < 0.5

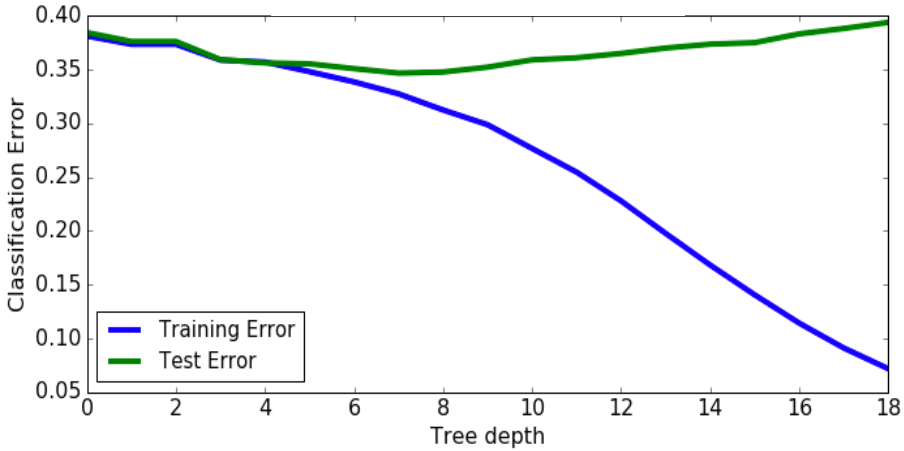
Not always possible

Extreme example: No classifier can separate a +1 on top of -1

Nonetheless, boosting often yields great training error

Overfitting in boosting

Decision trees on loan data

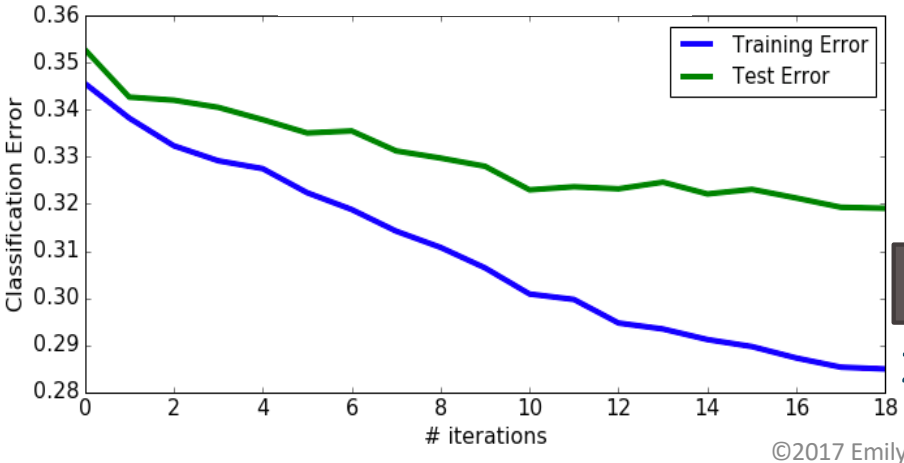


39% test error

Overfitting

8% training error

Boosted decision stumps on loan data

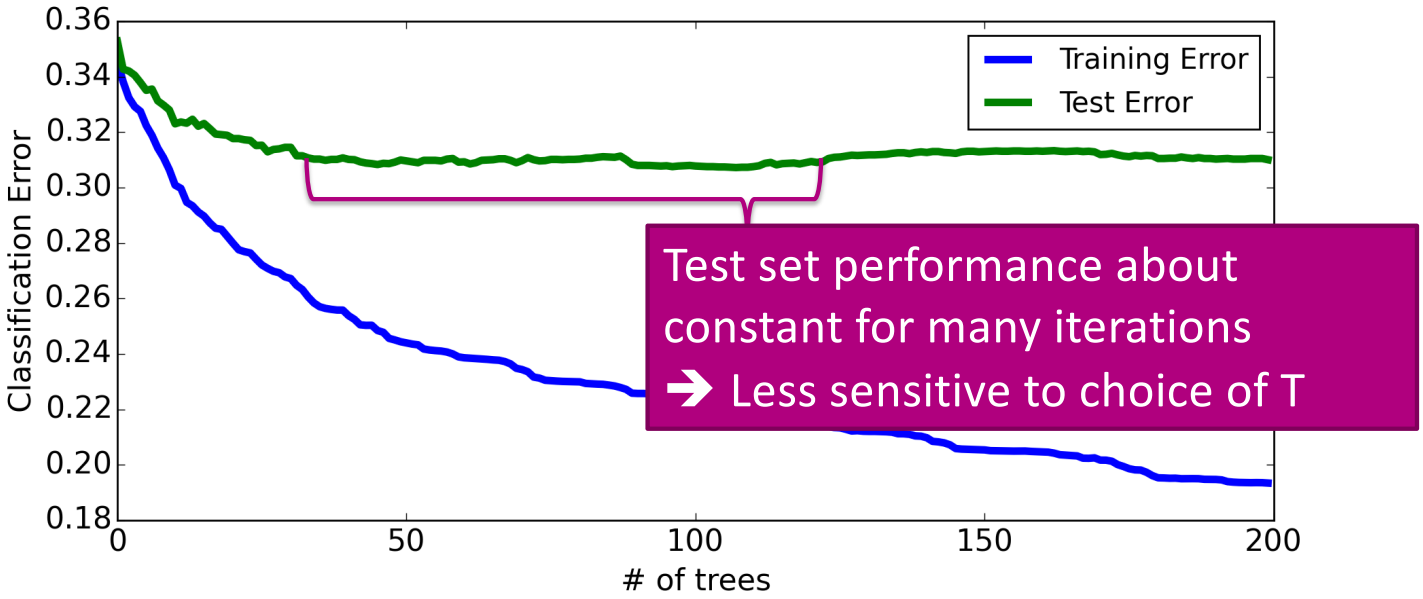


32% test error

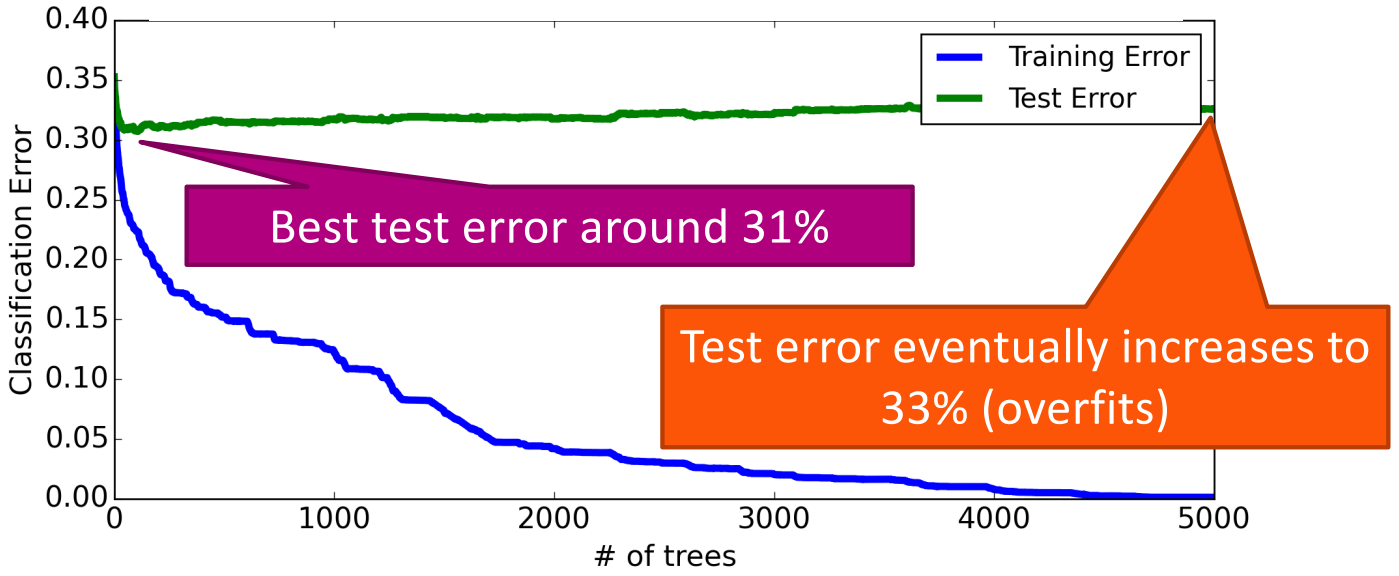
Better fit & lower test error

28.5% training error

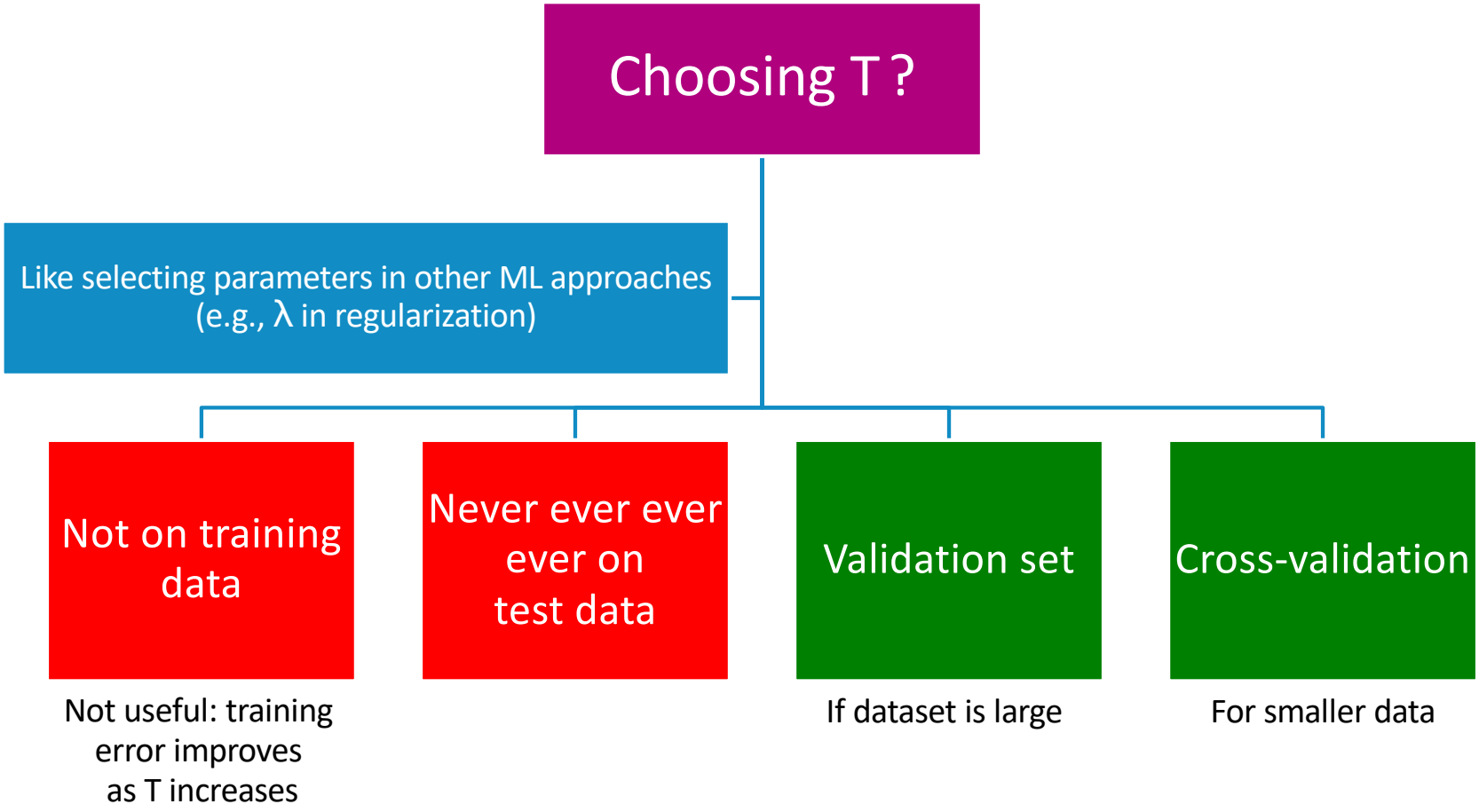
Boosting tends to be robust to overfitting



But boosting will eventually overfit, so must choose max number of components T



How do we decide when to stop boosting?



Summary of boosting

Variants of boosting and related algorithms

There are hundreds of variants of boosting, most important:

Gradient boosting

- Like AdaBoost, but useful beyond basic classification
- XGBoost (Tianqi Chen, UW)

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Many other approaches to learn ensembles, most important:

Random forests

- Bagging: Pick random subsets of the data
  - Learn a tree in each subset
  - Average predictions
- Simpler than boosting & easier to parallelize
- Typically higher error than boosting for same # of trees (# iterations T)

Impact of boosting (*spoiler alert... HUGE IMPACT*)

Amongst most useful ML methods ever created

Extremely useful in computer vision

- Standard approach for face detection, for example

Used by most winners of ML competitions (Kaggle, KDD Cup,…)

- Malware classification, credit fraud detection, ads click through rate estimation, sales forecasting, ranking webpages for search, Higgs boson detection,…

Most deployed ML systems use model ensembles

- Coefficients chosen manually, with boosting, with bagging, or others

What you should know about today's material for final

- What a decision tree is, basic greedy approach to constructing them, what the decision boundary will look like if data is real-valued (axis-aligned partitions)
- Mitigating overfitting and high variance by limiting depth, pruning tree, bagging and random forests.
- Understand idea of ensemble classifier
- Outline the boosting framework –
  sequentially learn classifiers on weighted data. Key idea: put more weight on data points where making error.
- Understand the AdaBoost algorithm at a high level
  - Learn each classifier on weighted data
  - Compute coefficient of classifier
  - Recompute data weights
  - Normalize weights