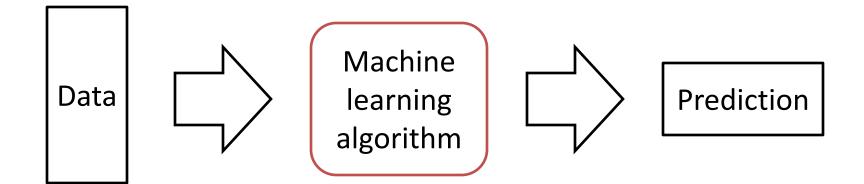
Random Forest Ensemble Visualization

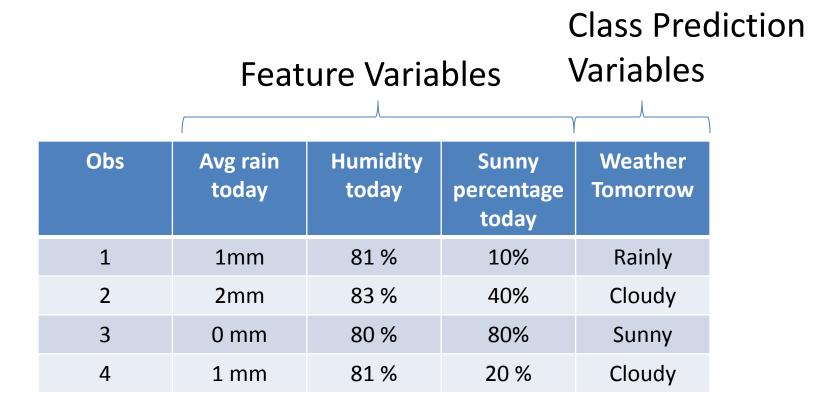
CPSC 547 Project

Ken Lau

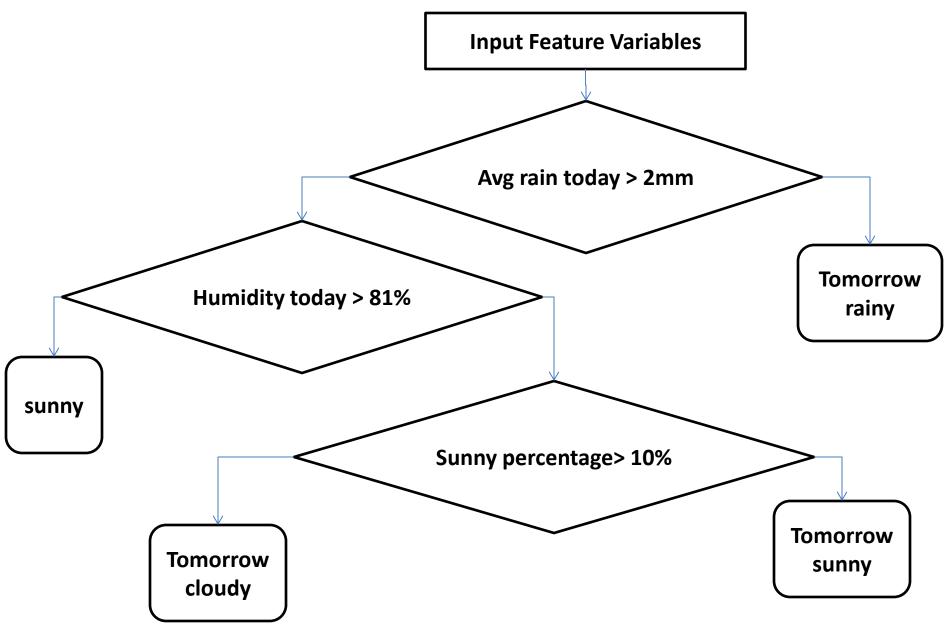
Prediction



Weather Data Example



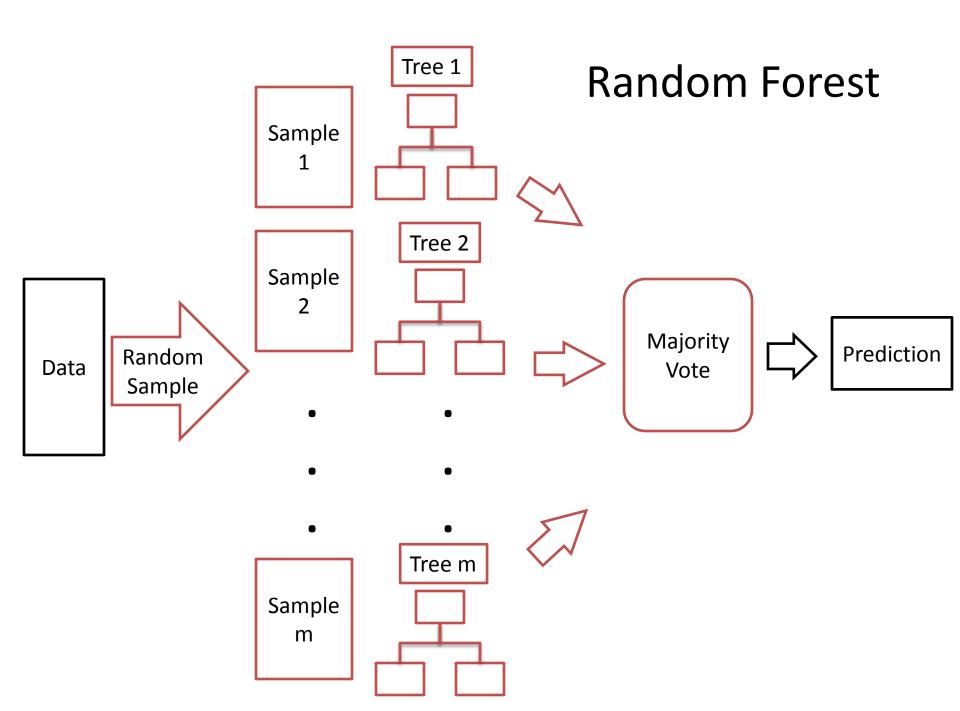
Classification Tree



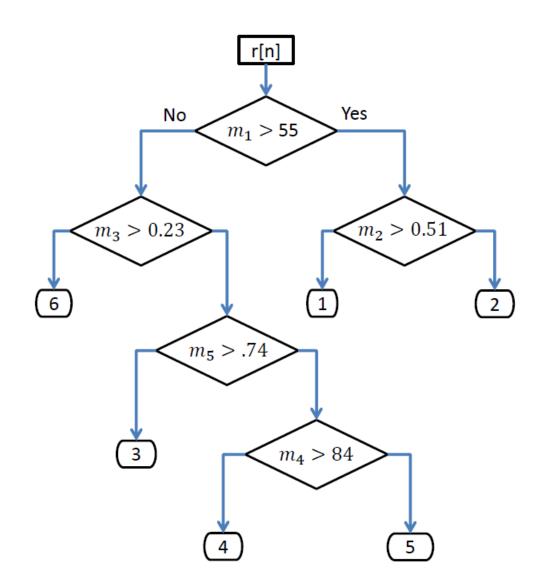
Random Forest

- Collection of classification trees

 Usually 500-1000
- Popular
- Black box



My Data

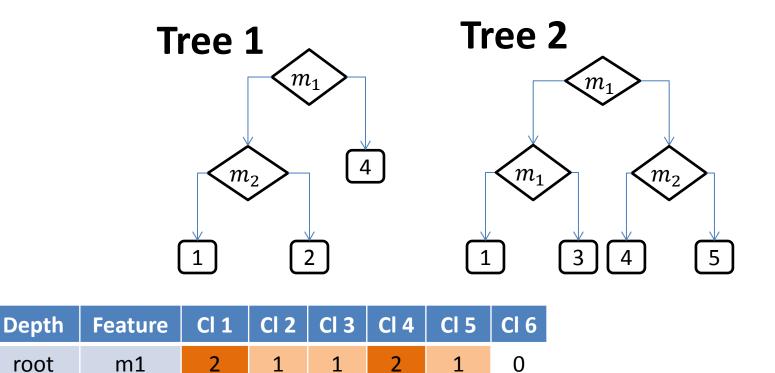


Problem:

How to visualize the collection of Classification trees

Aggregate: Features Variables Tree 2 Tree 1 m_1 m_1 Encode 4 m_2 m_1 m_2 **Colour Saturation** 2 5 1 3 1 4 Depth Appearance Feature Data Derive root m1 Depth Left Split Parent Feature **Right Split** 2 m1 m2 1 1 Depth Left Split **Right Split** Parent Feature 2 0 m1 m1 1

Aggregate: Class Prediction Variables



Dept	h Parent	Feature	Cl 1	Cl 2	Cl 3	CI 4	CI 5	CI 6
2	m1	m2	1	1	0	1	1	0
Dept	h Parent	Feature	Cl 1	CI 2	CI 3	CI 4	Cl 5	CI 6

Visualization

start																	
m5 root:		root: 172			c	class-1: 8608		class-2: 8638		class-3: 8535		class-4: 8675		class-5: 8455		class-6: 8689	
T	m1	left-split:	56	right-split: 60		class-1: 2963	L.	class-2: 3013		class-3: 2810)	class-4: 2897	,	class-5: 3083	3	class-6: 2845	5
	m3	left-split:	62	right-split: 18		class-1: 926		class-2: 960		class-3: 2388	;	class-4: 3052	2	class-5: 1424	4	class-6: 3047	7
	m4	left-split:	9	right-split: 61		class-1: 3057	,	class-2: 3022		class-3: 1237	7	class-4: 449		class-5: 2058	3	class-6: 466	
	m2	left-split:	12	right-split: 32		class-1: 1618		class-2: 1597		class-3: 950		class-4: 561		class-5: 1478	3	class-6: 599	
	m5	left-split:	33	right-split: 1		class-1: 44		class-2: 46		class-3: 1150		class-4: 1716	;	class-5: 412		class-6: 1732	2
m	1	root: 169			0	ass-1: 8425	c	lass-2: 8442	d	ass-3: 8493	d	ass-4: 8438	d	ass-5: 8444	d	lass-6: 8458	
m	4	root: 83			0	lass-1: 4198	c	lass-2: 4362	d	ass-3: 4043	d	ass-4: 4064	d	ass-5: 4066	d	lass-6: 4167	
m	3	root: 72			0	lass-1: 3530	c	lass-2: 3436	d	ass-3: 3803	d	ass-4: 3566	d	ass-5: 3670	d	lass-6: 3595	
m	2	root: 4			•	lass-1: 216	c	lass-2: 173	d	ass-3: 177	d	ass-4: 191	d	ass-5: 242	d	lass-6: 201	

• So What?

- Feature importance and interaction
- Tree pruning when non-uniform class count distribution occurs
- Class count predictions given nodes traversed so far

Software

- Python
 - Model fitting
 - Information retrieval
 - Aggregation

- D3
 - Encoding

- Based on Indented Tree (Mike Bostock, 2011) http://bl.ocks.org/mbostock/1093025

Demo

Visualization link: http://kenlau177.github.io/Indented-Agg-Tree/

Scale

- Manageable up to trees of depth 8 with 5 feature variables.
 - Out of memory issue
 - There is a step that generates all possible permutations of features variables
 - Instead keep only variables that appear at least once in the collection of trees
- Handles more than 1000 trees fast with depth less than 7

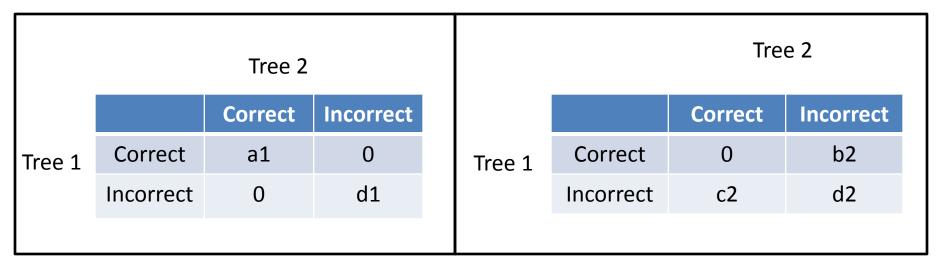
Number of Trees	Depth	Time					
200	7	59 sec					
800	3	10 sec					
1500	3	15 sec					
1500	6	22 sec					

Quantify the Tree Ensembles

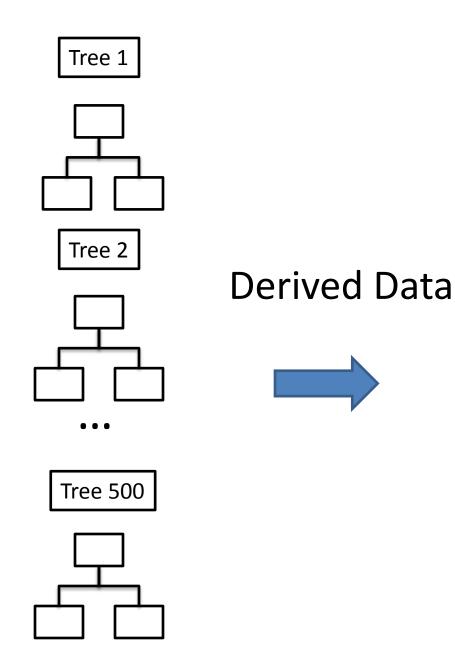
- Measure diversity among trees based on class predictions
- Unrelated members are the reason for high accuracy
- Hamann Similarity Measure
 - Multivariate version

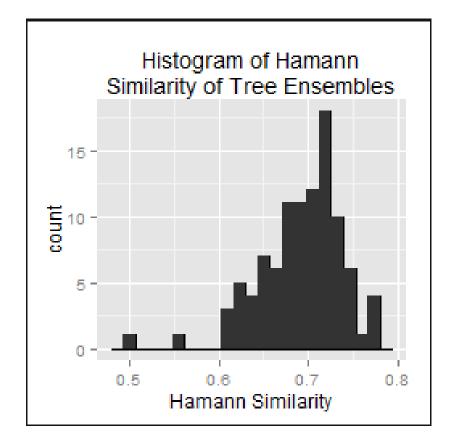
Predicted **Same** Class

Predicted **Different** Class

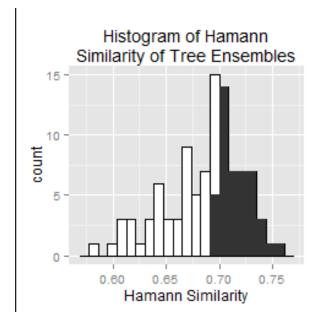


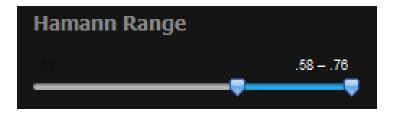
$$H = \frac{(a_1 + d_1) - (b_2 + c_2 + d_2)}{a_1 + d_1 + b_2 + c_2 + d_2}$$



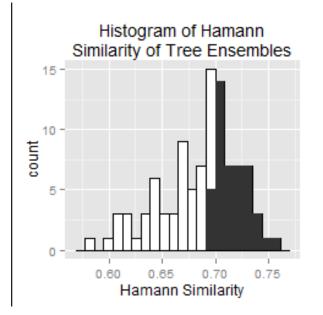


Filter Trees based on Hamann Similarity

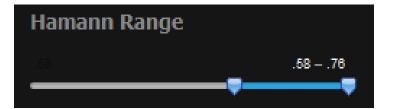




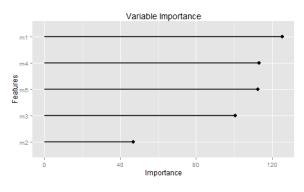
Filter Trees based on Hamann Similarity



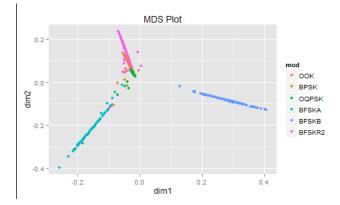




Variable Importance



Multi-dimensional scaling



Thank you

R Shiny App: https://kenlau177.shinyapps.io/randomForestApp/