

Feature interactions

Example: banner selection

...	category_ad	category_site	...	is_clicked
...	auto_part	game_news	...	0
...	music_tickets	music_news	..	1
...	mobile_phones	auto_blog	...	0

Example: banner selection

...	category_ad	category_site	...	is_clicked
...	auto_part	game_news	...	0
...	music_tickets	music_news	..	1
...	mobile_phones	auto_blog	...	0

...	ad_site	...	is_clicked
...	auto_part game_news	...	0
...	music_tickets music_news	..	1
...	mobile_phones auto_blog	...	0

Example of interactions

f1	f2
A	X
B	Y
B	Z
A	Z

Example of interactions

f1	f2
A	X
B	Y
B	Z
A	Z

Join

f_join
A X
B Y
B Z
A Z

OneHot
(f_join)

A X	B Y	B Z	A Z
1			
	1		
		1	
			1

Example of interactions

f1	f2
A	X
B	Y
B	Z
A	Z

OneHot(f1),
OneHot(f2)

A	B
1	
	1
	1
1	

X	Y	Z
1		
	1	
		1
		1

Pairwise columns
multiplications

AX	AY	AZ	BX	BY	BZ
1					
				1	
					1
		1			

Example of interactions

f1	f2		f_join
1.2	0.0		0.0
3.4	0.1	Mul	0.34
5.6	1.0		5.6
7.8	-1.0		-7.8

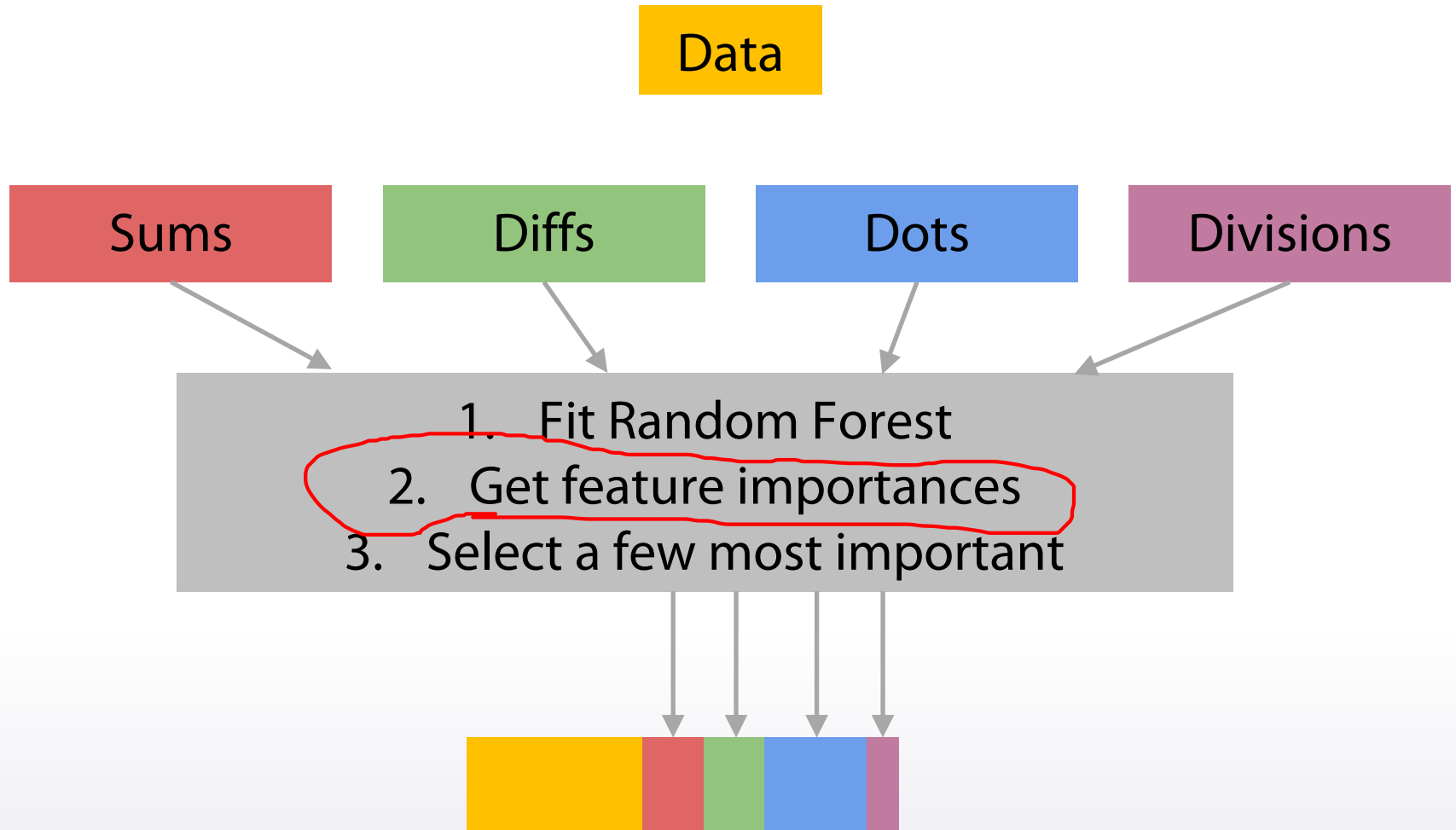
Frequent operations for feature interaction

- Multiplication
- Sum
- Diff
- Division

Practical Notes

- We have a lot of possible interactions – $N*N$ for N features.
 - a. Even more if use several types in interactions
- Need to reduce its' number
 - a. Dimensionality reduction
 - b. Feature selection

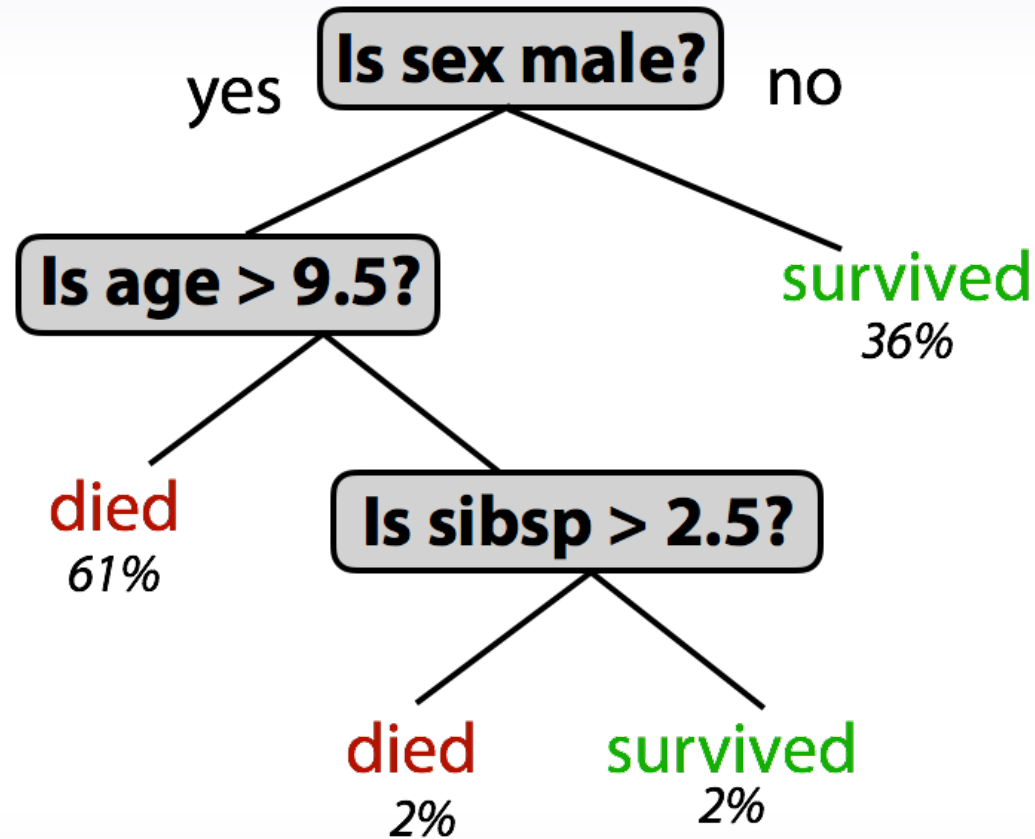
Example of interaction generation pipeline



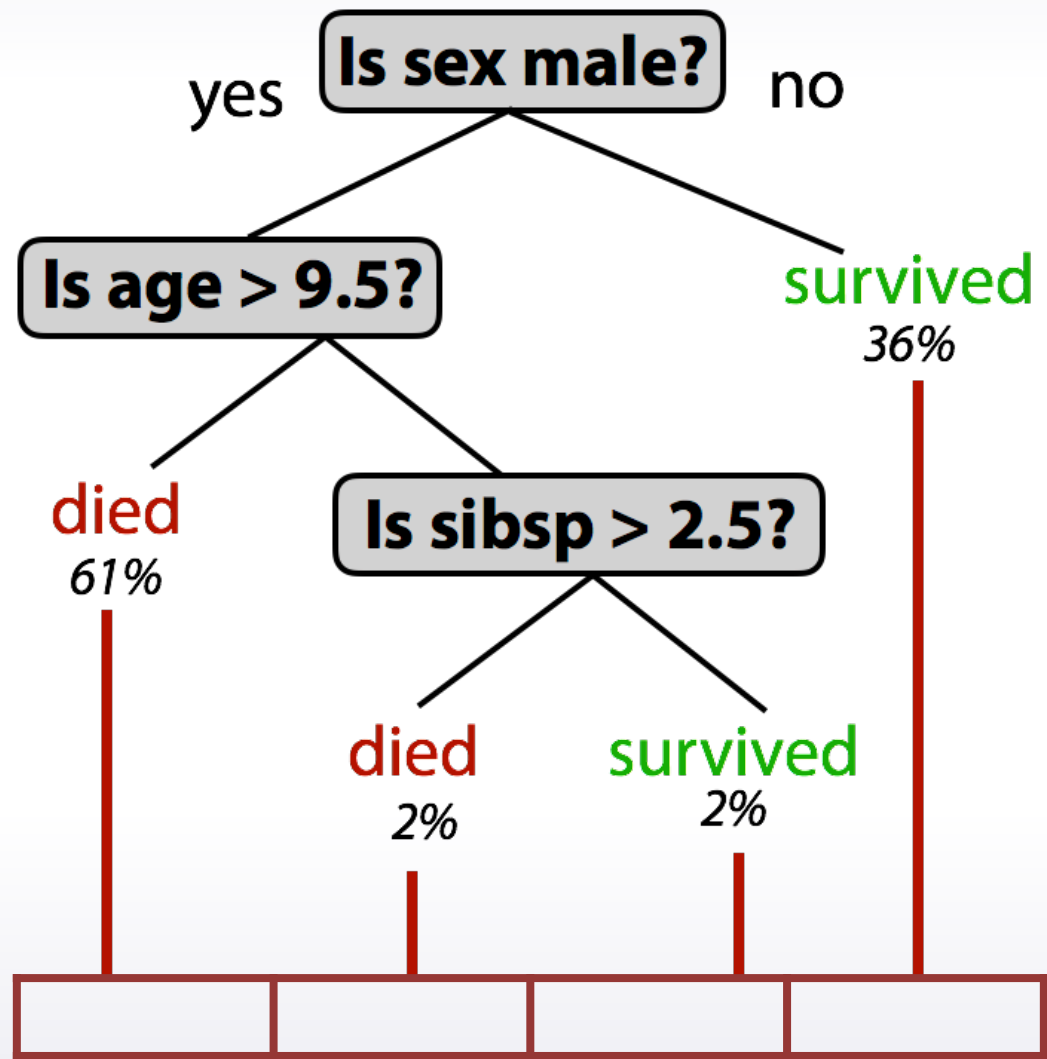
Interactions' order

- We looked at 2nd order interactions.
- Such approach can be generalized for higher orders.
- It is hard to do generation and selection automatically.
- Manual building of high-order interactions is some kind of art.

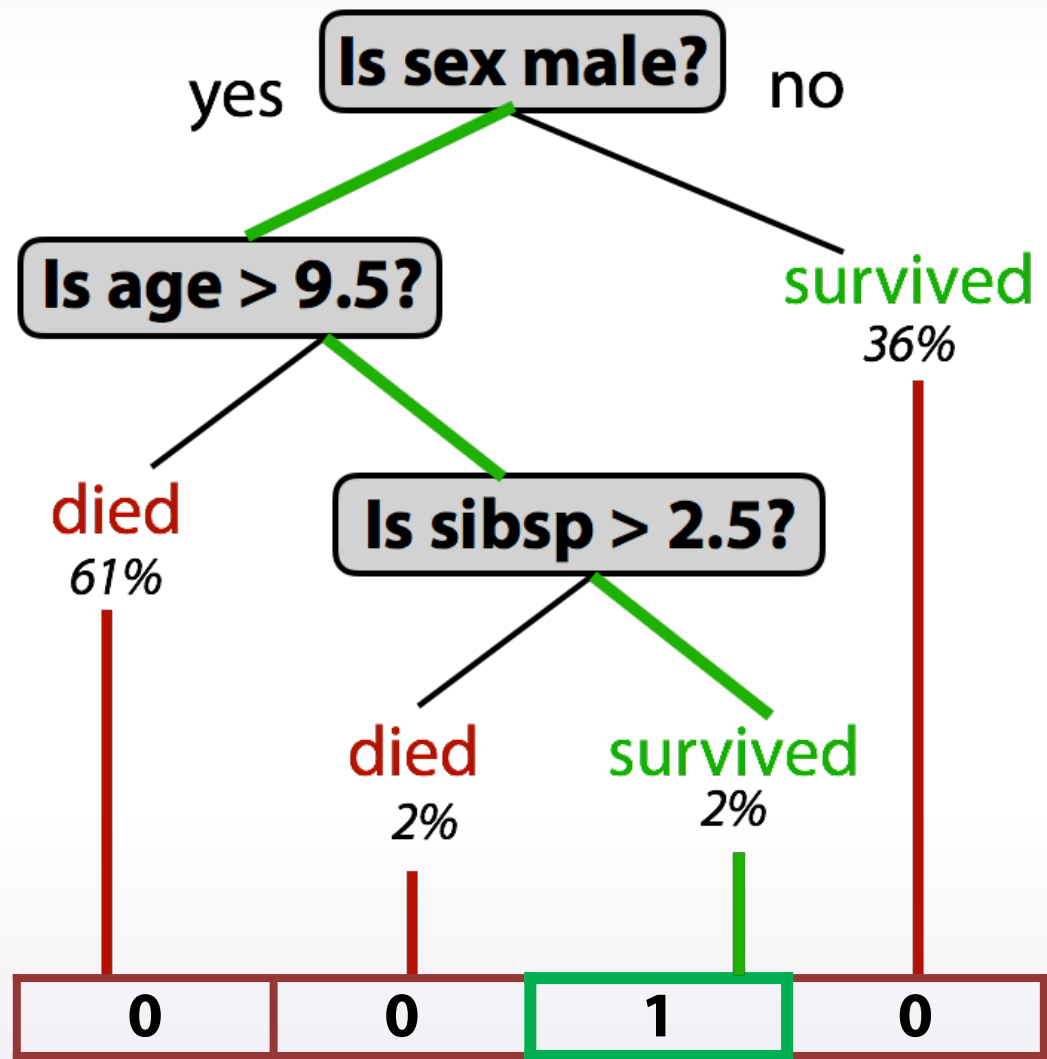
Extract features from DT



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Extract features from DT



How to use it

In sklearn:

```
| tree_model.apply( )
```

In xgboost:

```
| booster.predict(pred_leaf=True)
```

Conclusion

- We looked at ways to build an interaction of categorical attributes
- Extended this approach to real-valued features
- Learn how to extract features via decision trees