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

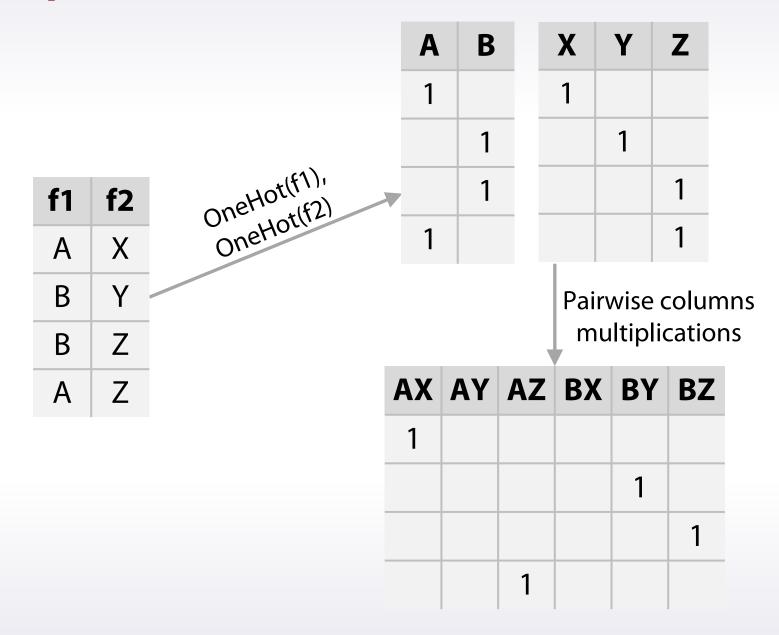
Example: banner selection

•••	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_tikets music_news	••	1
•••	mobile_phones auto_blog	•••	0

f1	f2
Α	X
В	Y
В	Z
Α	Z

f1	f2		f_join		A X	B Y	B Z	A Z
Α	Χ		A X	OneHot	1			
В	Y	Join	B Y	(f_join)		1		
В	Z		B Z				1	
Α	Z		A Z					1



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

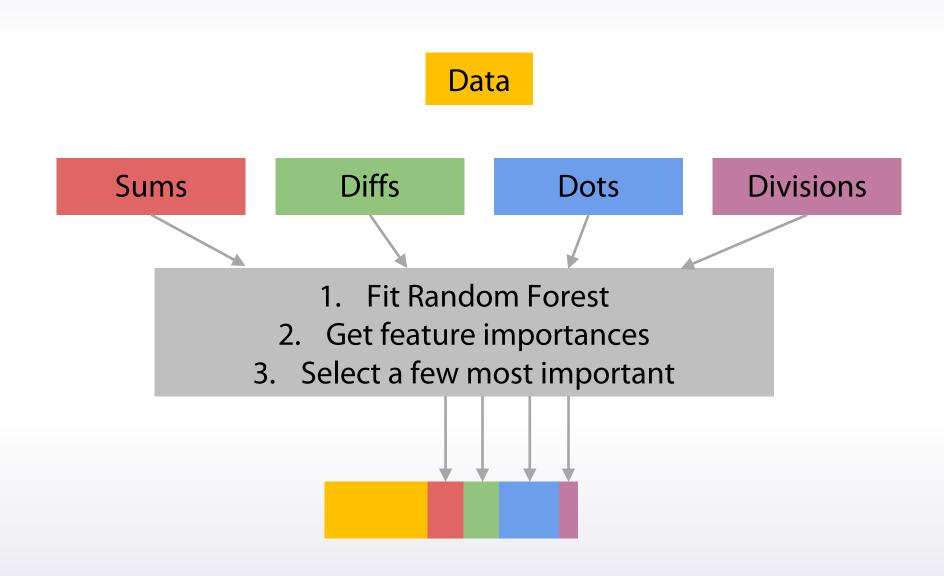
Frequent operations for feature interaction

- 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

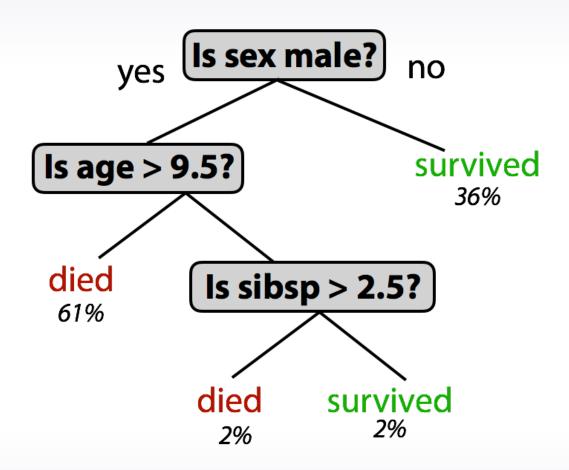
Example of interaction generation pipeline



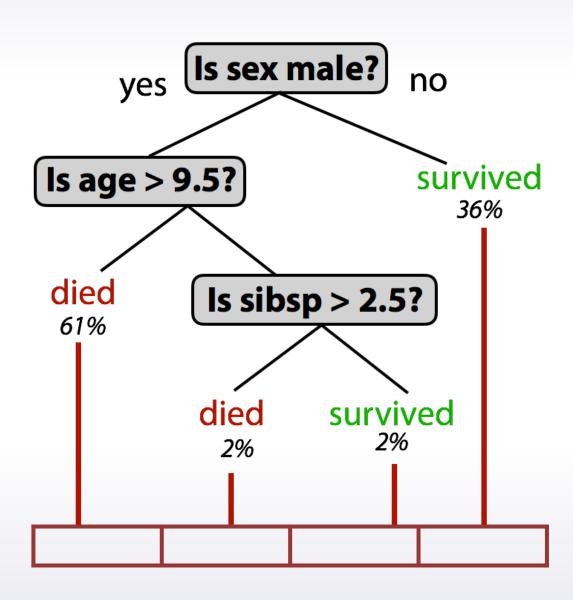
Interactions' order

- 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.

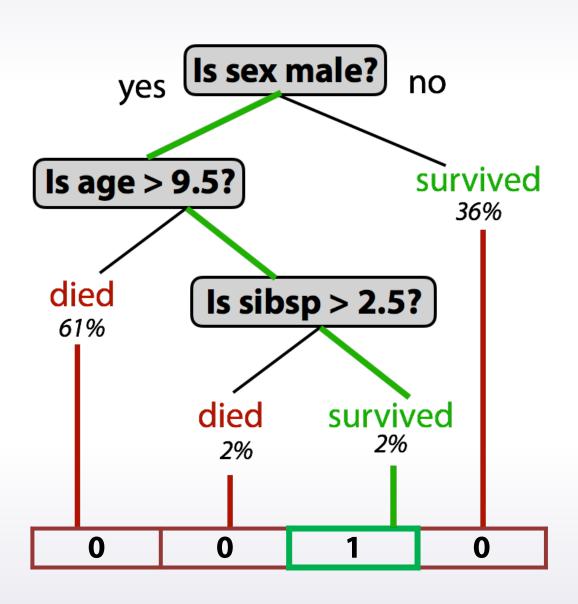
Extract features from DT



Extract features from DT



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