$egin{array}{ll} {\it Date} & {\it 20} \ {\it M} \ {\it T} \ {\it W} \ {\it T} \ {\it F} \ {\it S} \ {\it S} \ \end{array}$ 31/10 Ensemble Learning Mid copies - feedbacks, different opinione for how correting is interple for you - LR - ne combine différent opinions - cumulative - NN e.g. sale a property property value après 5 values - enn - Ensemble (partial) take average of different spinions This is Ensembling - voting also provice, professionals / experts -> opinion inclined cowonds experts 13 - unis is neighted ensembling expect opinion is 3x that of novice - A single model in sometimes not enough to recognize data Mony simples models are trained to to understand parts
of data and results are combined. -> better accuracy I computational power, resources required - Ensemble is type of divide and conquer netwood - models can se same like secision Tree - bright dataset and different models -> Ensemble rechniques: - different model on came data 1) Taking mode of the results: voting scheme - we keep it add

Date20_ M T W T F S S
2) Taking average of the results:
2) Taking average of the results: somerage of medictions from all models -> final mediction
For regression problem, this could be used
3) Taking neighted average of the results:
3) Taking weighted average of the result : > models one assigned neights on basis of their importance
model meights are hyperponameters
some arrighed emselver
Models one not equally powerful
=> Advanced Ensemble Techniques:
- Train same data model multiple times on different.
dala cels
i) Bookshapping aggregating :/ bagging:
Split in hain/test
J
subjeté - Take mean
data
剪
2) Random Foresti
- hain decision hee
3) Boosting:
subcets -> apply weak lenner -> mistakes on data points
model new « re-train to increase meights cearns the
mistakes pomis

	Date 20 M T W T F S S
- Ensemble techniques reduce raionne so no pr	roblem overfia
- Subseli of the samples ? subseli	•
- Subsets of the samples ? subsets - Subsets of the featines I ways	
V	, pr
→ Romdom Fonest:	
- it spill feat data in both ways	
	. !
- it uses bagging on jealines e.g. 100 fealines subset -> DT laga diga	-> e2 p2
- hees will be different out depth should	be same
- hees will be different out depth should - how dot ne different features se learn ki	ya hoga
→ Boostry:	1 -
- Jourses on classification problems XGROOST (Extreme Gradient Boost)	,
XGROOST (Extieme Gradient Boott)	-
	3
9	•
· · · · · · · · · · · · · · · · · · ·	
	^
	, ,
	5 F

3/11 Ensemble learning Date: DDMMYY
split a big problem into a set of emple problems
-> handom Fonest
do 11 on DTc
depar of all hees must be same
1. 1. 1-IT is so that endcome is at the same
more depth - over jithing time les depth - anderfitting
len depa - underfitting
port-pruning, pre-pruning
-> Ado Boosting:
input - it is threshold
classifier > function $f(n)$ can be different in
- mitially equal neights - meights are probabilités itérations
- ilévations from 1 lo 7 (no.0) examples).
- Then we update the probabilities
- We see examples which have been misclassified
- We update threshold in each 'dévations
- sum samplei's protobilities which have been misclassified
Et -> error lein dt -> com be a learning rate
can be
* calculator
Stopping ailtria -> when no enors
Teacher's Signature