Ensemble methods: StackNet

By Marios Michailidis



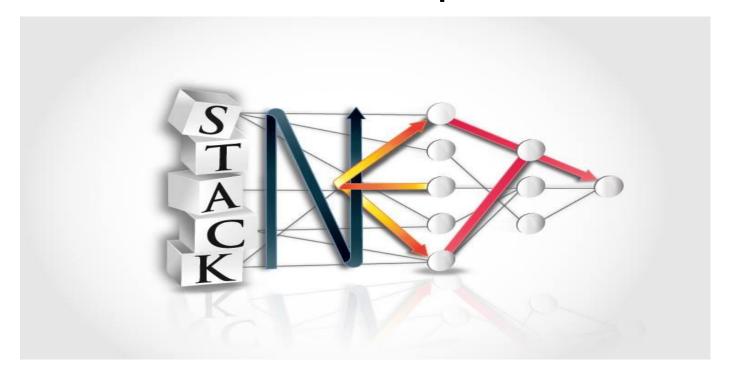
Examined ensemble methods

- Averaging (or blending)
- Weighted averaging
- Conditional averaging
- Bagging
- Boosting
- Stacking
- StackNet



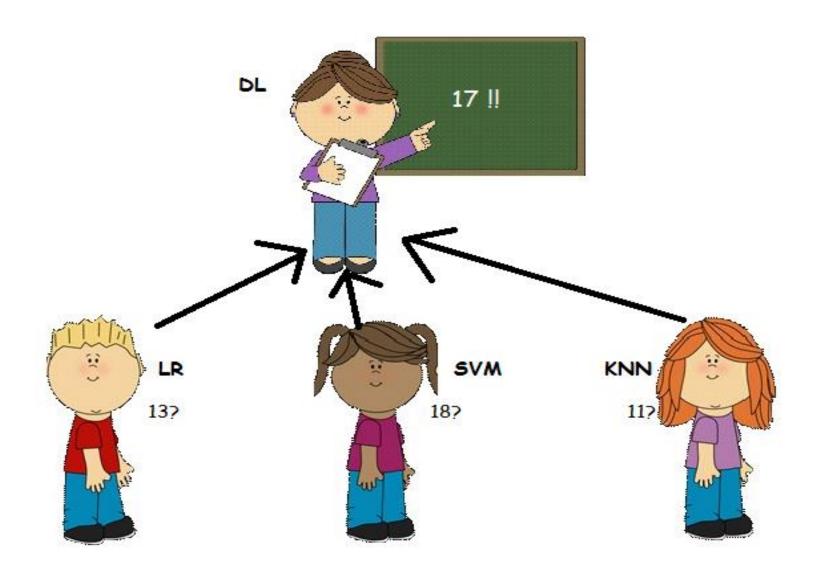
What is StackNet

A scalable meta modelling methodology that utilizes stacking to combine multiple models in a neural network architecture of multiple levels.



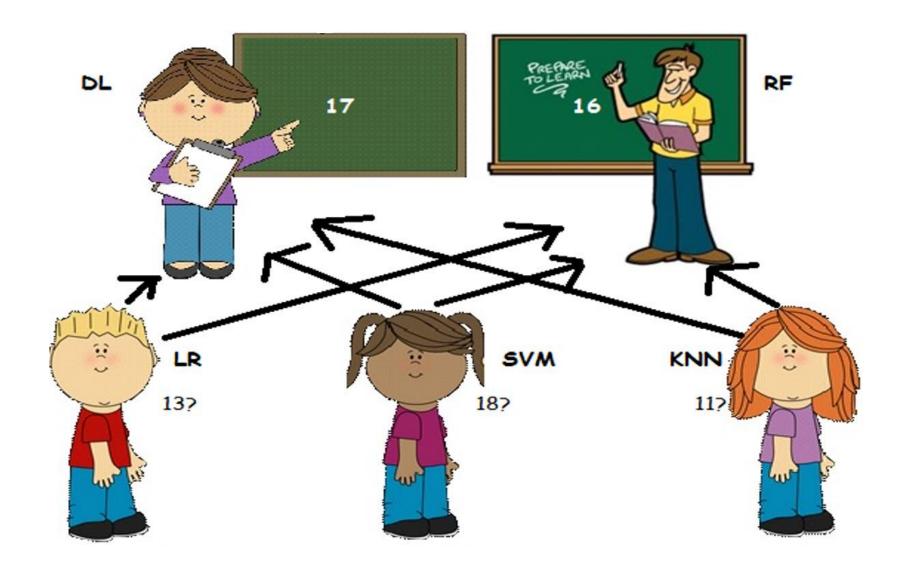


(Continuing) Naïve example



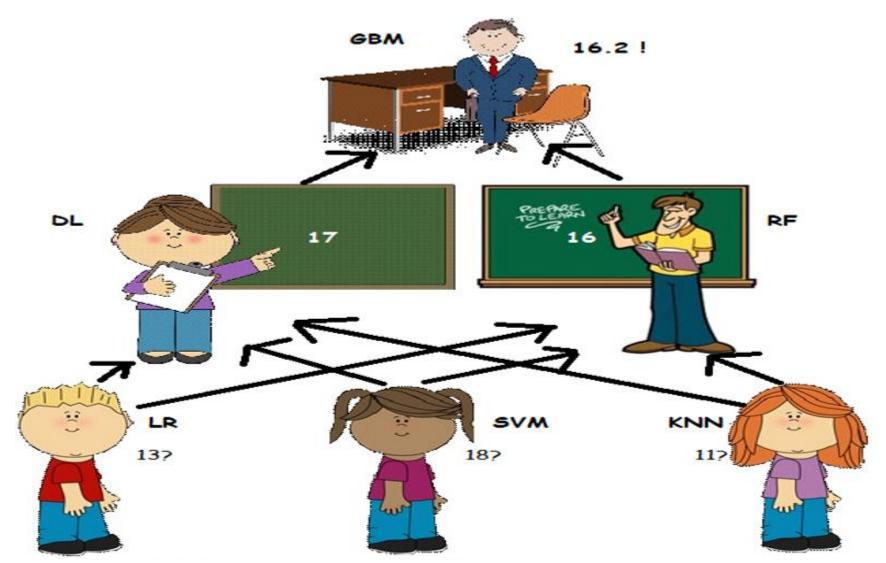


(Continuing) Naïve example



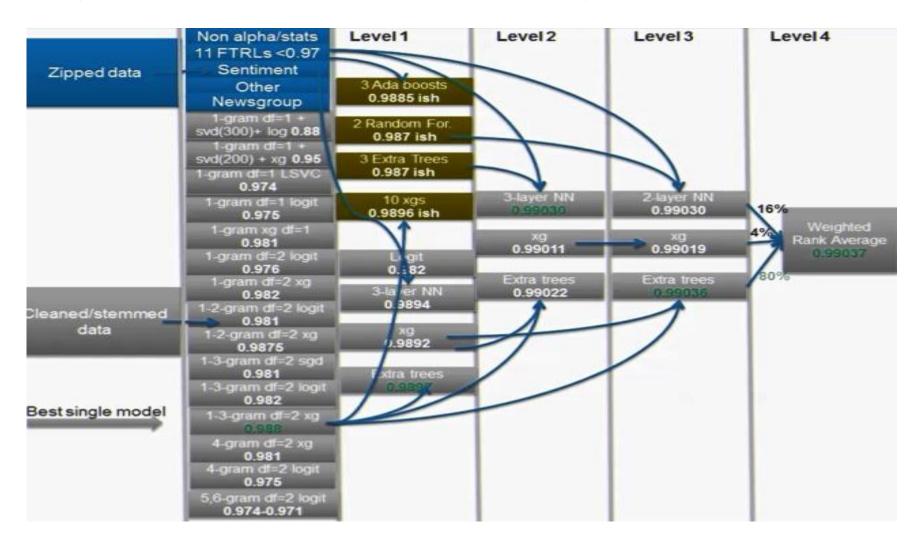


(Continuing) Naïve example





Why would this be of any use



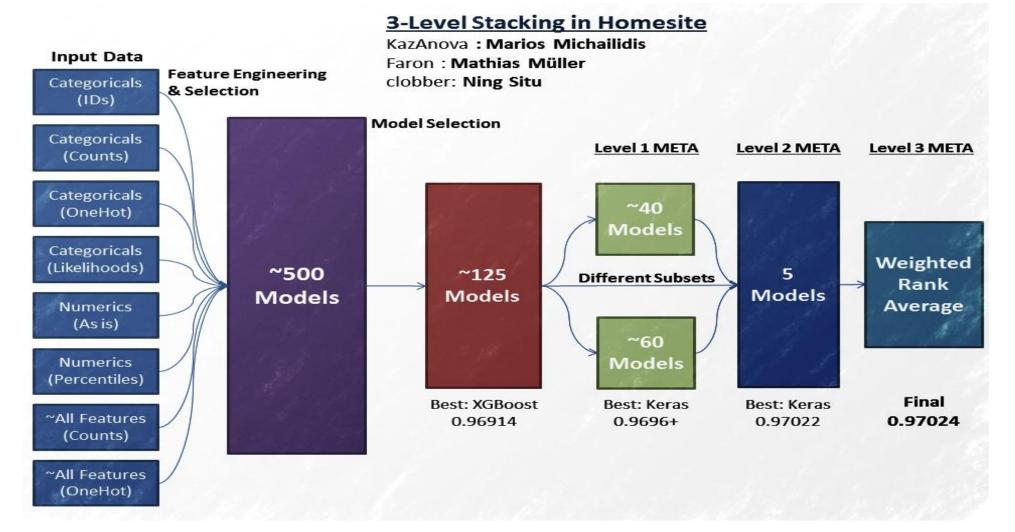


I'm giving you an example of a competition my team used, four layer of stacking, in order to win. And we used two different sources of input data.

We generated multiple models. Normally, exit boost and logistic regressions, and then we fed those into a four-layer architecture in order to get the top score. And although we could have escaped without using that fourth layer, we still need it up to level three in order to win. So you can understand the usefulness of deploying deep stacking.

Another example is the Homesite competition organized by Homesite insurance where again, we created many different views of the data. So we had different transformations. We generated many models. We fed those models into a three-level architecture. I think we didn't need the third layer again. Probably, we could have escaped with only two levels but again, deep stacking was necessary in order to win. So there is your answer, deep stacking on multiple levels really helps you to win competitions.

Why would this be of any use





Why would this be of any use

3-Level Stacking in Homesite

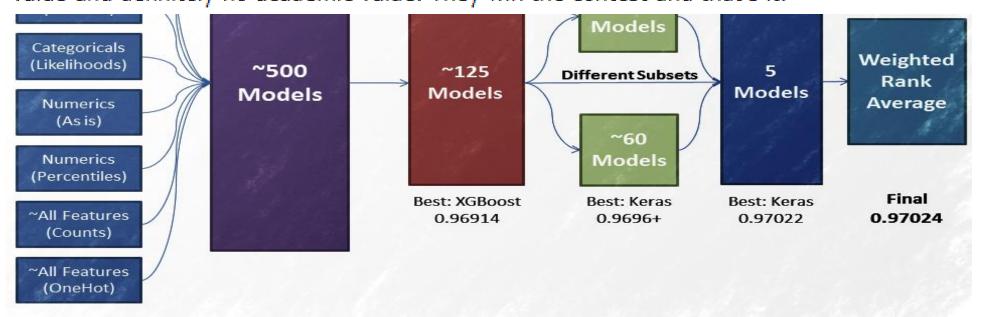
KazAnova: Marios Michailidis

Faron : Mathias Müller

Feature Engineering

Input Data

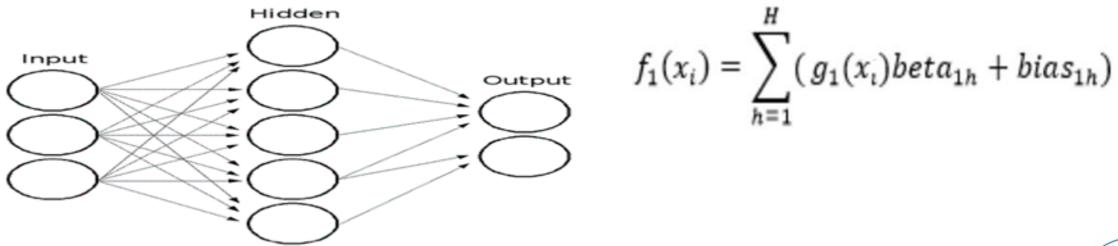
These contests that are so close to 100% scores encourage massive, ugly ensembles consisting of old tech that's existed for many years, just to shave off those last fractions of a percent. They result in virtually no commercial value and definitely no academic value. They win the contest and that's it.





StackNet as a neural network

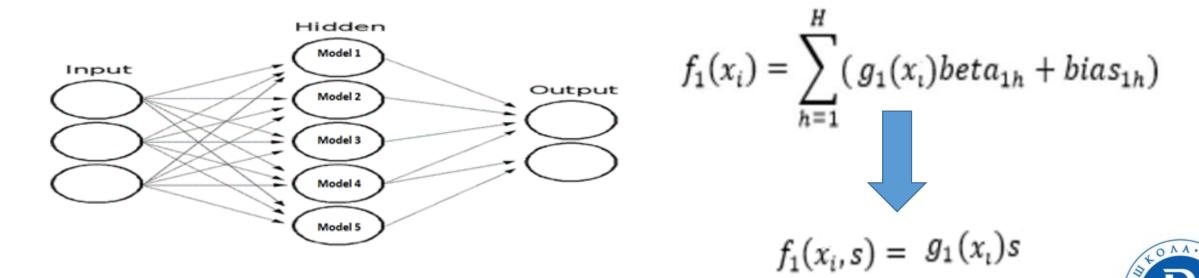
- In a neural network, every node is a **simple linear model** (like linear regression) with some non linear transformation.
- Instead of a linear model we could use any model.





StackNet as a neural network

- In a neural network, every node is a **simple linear model** (like linear regression) with some non linear transformation.
- Instead of a linear model we could use any model.



- We cannot use **BP** (not all models are differentiable)
- We use **stacking** to link each model/node with target



Train data



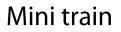
Training data

Valid data



Training data







Mini valid





x0	x 1	x2	х3	у
0.94	0.27	0.80	0.34	1
0.02	0.22	0.17	0.84	0
0.83	0.11	0.23	0.42	1
0.74	0.26	0.03	0.41	0
0.08	0.29	0.76	0.37	0
0.71	0.76	0.43	0.95	1
0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1



K=4

х0	x 1	x2	х3	у
0.94	0.27	0.80	0.34	1
0.02	0.22	0.17	0.84	0
0.83	0.11	0.23	0.42	1
0.74	0.26	0.03	0.41	0
0.08	0.29	0.76	0.37	0
0.71	0.76	0.43	0.95	1
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0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1

0.00 0.00 0.00 0.00 0.00 0.00



Fold	•	1	

x0	x 1	x2	х3	у
0.94	0.27	0.80	0.34	1
0.02	0.22	0.17	0.84	0
0.83	0.11	0.23	0.42	1
0.74	0.26	0.03	0.41	0
0.08	0.29	0.76	0.37	0
0.71	0.76	0.43	0.95	1
0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1

pred	
0.00	
0.00	
0.00	
0.00	
0.00	
0.00	
0.00	
0.00	



х0	x 1	x2	х3	у					
0.94	0.27	0.80	0.34	1					
0.02	0.22	0.17	0.84	0					
0.83	0.11	0.23	0.42	1	0.83	0.11	0.23	0.42	1
0.74	0.26	0.03	0.41	0	0.74	0.26	0.03	0.41	0
0.08	0.29	0.76	0.37	0	0.08	0.29	0.76	0.37	0
0.71	0.76	0.43	0.95	1	0.71	0.76	0.43	0.95	1
0.08	0.72	0.97	0.04	0	0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1	0.84	0.79	0.89	0.05	1

pred	
0.00	
0.00	
0.00	
0.00	
0.00	
0.00	
0.00	
0.00	



Fold:1

					0.94	0.27	0.80	0.34	1
х0	x1	x2	х3	у	0.02	0.22	0.17	0.84	0
0.94	0.27	0.80	0.34	1					
0.02	0.22	0.17	0.84	0					
0.83	0.11	0.23	0.42	1	0.83	0.11	0.23	0.42	1
0.74	0.26	0.03	0.41	0	0.74	0.26	0.03	0.41	0
0.08	0.29	0.76	0.37	0	0.08	0.29	0.76	0.37	0
0.71	0.76	0.43	0.95	1	0.71	0.76	0.43	0.95	1
0.08	0.72	0.97	0.04	0	0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1	0.84	0.79	0.89	0.05	1

Predict

pred
0.00
0.00
0.00
0.00
0.00
0.00
0.00
0.00



Fold:1

					0.94	0.27	0.80	0.34	1
х0	x1	x2	х3	у	0.02	0.22	0.17	0.84	0
0.94	0.27	0.80	0.34	1					
0.02	0.22	0.17	0.84	0					
0.83	0.11	0.23	0.42	1	0.83	0.11	0.23	0.42	1
0.74	0.26	0.03	0.41	0	0.74	0.26	0.03	0.41	0
0.08	0.29	0.76	0.37	0	0.08	0.29	0.76	0.37	0
0.71	0.76	0.43	0.95	1	0.71	0.76	0.43	0.95	1
0.08	0.72	0.97	0.04	0	0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1	0.84	0.79	0.89	0.05	1

Predict

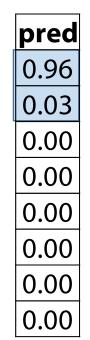
pred	
0.96	
0.03	
0.00	
0.00	
0.00	
0.00	
0.00	
0.00	



Fold: 2

					0.83	0.11	0.23	0.42	1
х0	x1	x2	х3	у	0.74	0.26	0.03	0.41	0
0.94	0.27	0.80	0.34	1					
0.02	0.22	0.17	0.84	0					
0.83	0.11	0.23	0.42	1	0.94	0.27	0.80	0.34	1
0.74	0.26	0.03	0.41	0	0.02	0.22	0.17	0.84	0
0.08	0.29	0.76	0.37	0	0.08	0.29	0.76	0.37	0
0.71	0.76	0.43	0.95	1	0.71	0.76	0.43	0.95	1
0.08	0.72	0.97	0.04	0	0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1	0.84	0.79	0.89	0.05	1

Predict





Fold: 2

					0.83	0.11	0.23	0.42	1
х0	x1	x2	х3	у	0.74	0.26	0.03	0.41	0
0.94	0.27	0.80	0.34	1					
0.02	0.22	0.17	0.84	0					
0.83	0.11	0.23	0.42	1	0.94	0.27	0.80	0.34	1
0.74	0.26	0.03	0.41	0	0.02	0.22	0.17	0.84	0
0.08	0.29	0.76	0.37	0	0.08	0.29	0.76	0.37	0
0.71	0.76	0.43	0.95	1	0.71	0.76	0.43	0.95	1
0.08	0.72	0.97	0.04	0	0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1	0.84	0.79	0.89	0.05	1

Predict

Train

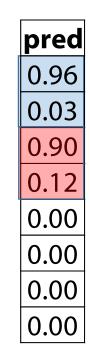
0.96 0.03 0.90 0.12 0.00 0.00 0.00



Fold: 3

					0.08	0.29	0.76	0.37	0
x0	x1	x2	х3	у	0.71	0.76	0.43	0.95	1
0.94	0.27	0.80	0.34	1					
0.02	0.22	0.17	0.84	0					
0.83	0.11	0.23	0.42	1	0.94	0.27	0.80	0.34	1
0.74	0.26	0.03	0.41	0	0.02	0.22	0.17	0.84	0
0.08	0.29	0.76	0.37	0	0.83	0.11	0.23	0.42	1
0.71	0.76	0.43	0.95	1	0.74	0.26	0.03	0.41	0
0.08	0.72	0.97	0.04	0	0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1	0.84	0.79	0.89	0.05	1

Predict





Fold: 3

					0.08	0.29	0.76	0.37	0
x0	x 1	x2	х3	у	0.71	0.76	0.43	0.95	1
0.94	0.27	0.80	0.34	1					
0.02	0.22	0.17	0.84	0					
0.83	0.11	0.23	0.42	1	0.94	0.27	0.80	0.34	1
0.74	0.26	0.03	0.41	0	0.02	0.22	0.17	0.84	0
0.08	0.29	0.76	0.37	0	0.83	0.11	0.23	0.42	1
0.71	0.76	0.43	0.95	1	0.74	0.26	0.03	0.41	0
0.08	0.72	0.97	0.04	0	0.08	0.72	0.97	0.04	0
0.84	0.79	0.89	0.05	1	0.84	0.79	0.89	0.05	1

Predict

Train

0.96 0.03 0.90 0.12 0.03 0.77 0.00 0.00



Fold:4

					0.08	0.72	0.97	0.04	0	ח
x0	x1	x2	х3	У	0.84	0.79	0.89	0.05	1	P
0.94	0.27	0.80	0.34	1						
0.02	0.22	0.17	0.84	0						
0.83	0.11	0.23	0.42	1	0.94	0.27	0.80	0.34	1	
0.74	0.26	0.03	0.41	0	0.02	0.22	0.17	0.84	0	
0.08	0.29	0.76	0.37	0	0.83	0.11	0.23	0.42	1	_
0.71	0.76	0.43	0.95	1	0.74	0.26	0.03	0.41	0	Т
0.08	0.72	0.97	0.04	0	0.08	0.29	0.76	0.37	0	
0.84	0.79	0.89	0.05	1	0.71	0.76	0.43	0.95	1	

Predict

	pred
	0.96
	0.03
	0.90
	0.12
	0.03
	0.77
,	0.00
	0.00



Fold:4

					0.08	0.72	0.97	0.04	0
x0	x1	x2	х3	у	0.84	0.79	0.89	0.05	1
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Predict

Train

0.96 0.03 0.90 0.12 0.03 0.77 0.18 0.91



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Predict

Train

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0.84	0.79	0.89	0.05	1	0.71	0.76	0.43	0.95	1

Predict

Train

test
0.43
0.03
0.90
0.12
0.03
0.77
0.18
0.91

0.96 0.03 0.90 0.12 0.03 0.77 0.18



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0.84	0.79	0.89	0.05	1	0.71	0.76	0.43	0.95	1

Predict

test
0.43
0.03
0.90
0.12
0.03
0.77
0.18
0.91

pred	pred
0.96	0.00
0.03	0.00
0.90	0.00
0.12	0.00
0.03	0.00
0.77	0.00
0.18	0.00
0.91	0.00

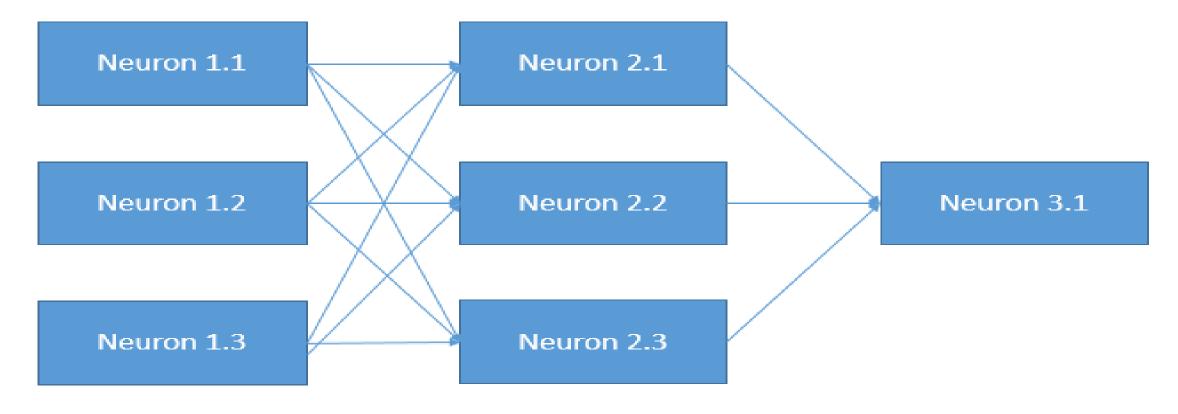


- We cannot use **BP** (not all models are differentiable)
- We use **stacking** to link each model/node with target
- To extend to many levels, we can use a Kfold paradigm

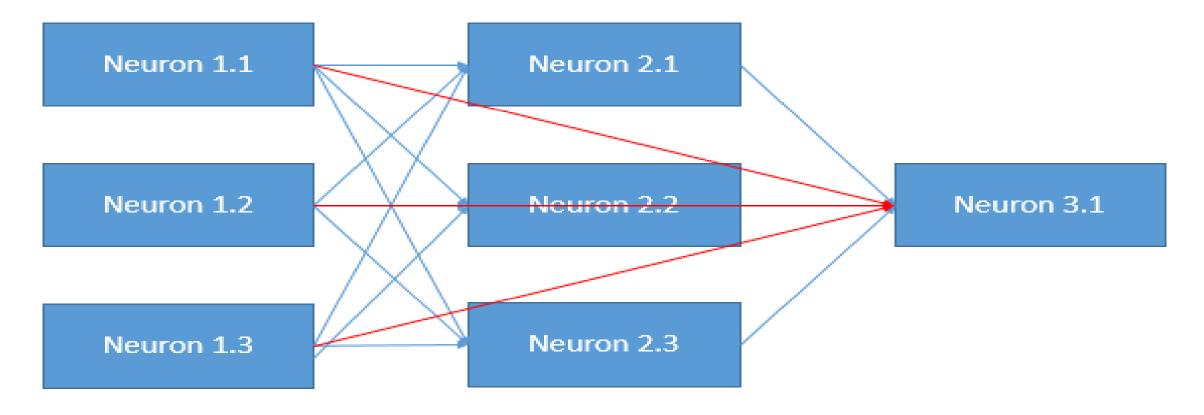


- We cannot use **BP** (not all models are differentiable)
- We use **stacking** to link each model/node with target
- To extend to many levels, we can use a Kfold paradigm
- No epochs different connections instead.











1st level tips

- Diversity based on algorithms:
 - ☐ 2-3 gradient boosted trees (lightgb, xgboost, H2O, catboost)
 - □2-3 Neural nets (keras, pytorch)
 - □ 1-2 ExtraTrees/Random Forest (sklearn)
 - □1-2 linear models as in logistic/ridge regression, linear svm (sklearn)
 - □1-2 knn models (sklearn)
 - □1 Factorization machine (libfm)
 - □1 svm with nonlinear kernel if size/memory allows (sklearn)
- Diversity based on input data:
 - □Categorical features: One hot, label encoding, target encoding, frequency
 - □Numerical features: outliers, binning, derivatives, percentiles, scaling
 - □Interactions : col1*/+-col2, groupby, unsupervised

Subsequent level tips

- Simpler (or shallower) Algorithms:
 - ☐ gradient boosted trees with small depth (like 2 or 3)
 - ☐ Linear models with high regularization
 - ☐ Extra Trees
 - ☐ Shallow networks (as in 1 hidden layer)
 - ☐ knn with BrayCurtis Distance
 - ☐ Brute forcing a search for best linear weights based on cv
- Feature engineering:
 - ☐ pairwise differences between meta features
 - ☐ row-wise statistics like averages or stds
 - ☐ Standard feature selection techniques
- For every 7.5 models in previous level we add 1 in meta (empirical)
- Be mindful of target leakage



Software for Stacking

- StackNet (https://github.com/kaz-Anova/StackNet)
- Stacked ensembles from H2O
- Xcessiv (https://github.com/reiinakano/xcessiv)



- It supports many prominent tools (xgboost, lightgbm, H2O, keras...)
- Can run classifiers in regression and vice versa.
- It has several top 10s in competitions.



		١	our submission sc	ored 0.92256.				
	ubmissio	bmission and Description		Private Score	Public Score Use for Final Score			
sub_70_30.7z 6 hours ago by Μαριος Μιχαηλιδης KazAnova add submission details			0.91923 0.92256					
#	Δpub	Team Name * in the money	Kernel	Team Me	mbers	Score	Entries	Las
1	-2	◆ Paul Duan & BS Man				0.92360	122	4
2	+ 1	* Owen Zhang			9	0.92273	54	4
3	-1	★ Dmitry&Leustagos		4	*	0.92255	110	4
4	~ 1	Tim			4	0.92189	24	4
5	-2	Chaotic Experiments			100	0.92154	77	4
6	-2	Murashka				0.92106	124	4
7	-3	Alexander Larko				0.92105	102	4
8	- 6	Gxav			L	0.92013	34	4
9	- 3	beginnersLuck			4	0.91961	76	4
10	~ 2	IzuiT			1	0.91942	32	4



- It supports many prominent tools (xgboost, lightgbm, H2O, keras...)
- Can run classifiers in regression and vice versa.
- It has several top 10s in competitions.
- The parameters' section.



XgboostClassifier

The original parameters can be found here

 $XgboostClassifier\ booster: gbtree\ num_round: 1000\ eta: 0.005\ max_leaves: 0\ gamma: 1.\ max_depth: 5\ min_child_weight: 1.0\ substitute and the substitute of the substit$

Parameter	Explanation
scale_pos_weight	used for imbalanced classes(double)
num_round	Number of estimators to build (int) . This is important.
max_leaves	Maximum leaves in a tree (int).
eta	Penalty applied to each estimator. Needs to be between 0 and 1 (double). This is important.
max_depth	Maximum depth of the tree (int). This is important.
subsample	Proportion of observations to consider (double). This is important.
colsample_bylevel	Proportion of columns (features) to consider in each level (double).
colsample_bytree	Proportion of columns (features) to consider in each Tree (double) This is important.
max_delta_step	controls optimization step (double).



Before we say goodbye...

- Apply what you have learnt (in competitions).
- It takes some time to adjust.
- Always save your code and re-use it
- Seek collaborations
- Read forums/kernels







Rank	Tier	User			Medals	;		Points
1	***** *******************************		You	joined a year ago	9 999	0	0	994,882
2	***		Stanislav Semenov	joined 4 years ago	2 8	9	0	190,356
3	***	gA ho	Μαριος Μιχαηλιδης KazAnova	joined 4 years ago	2 6	2 3	2 1	168,976
4	***		Faron	joined 3 years ago	1 4	4	3	132,862
5	***	9	Eureka	joined 4 years ago	(4) 16	1 3	3	131,759
6	***	3	raddar	joined 2 years ago	9	6	3	119,285
7	***	9	idle_speculation	joined 4 years ago	7	8	6	116,367
8	***	7	weiwei	joined a year ago	6 5	3	1	108,836
9	***		bestfitting	joined a year ago	6 5	3	0	107,497
10	***	9	Silogram	joined 5 years ago	1 0	2 4	9	97,850
11	888 888 888	121	utility	joined 3 years ago	1 3	7	3	95,855

