EEG/ERP & Machine Learning Regression Models

-a project framework testing on ChongQing EEG studies

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PNAS paper on RandomForest & PET



Persistent metabolic youth in the aging female brain

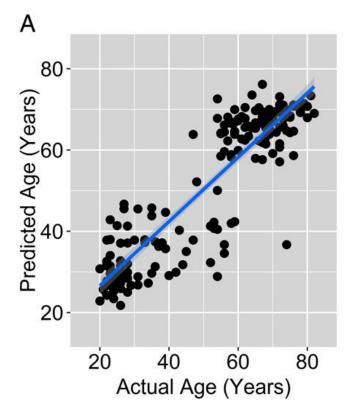
Manu S. Goyal^{a,b,1}, Tyler M. Blazey^a, Yi Su^a, Lars E. Couture^a, Tony J. Durbin^a, Randall J. Bateman^b, Tammie L.-S. Benzinger^a, John C. Morris^b, Marcus E. Raichle^{a,b}, and Andrei G. Vlassenko^a

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Sex differences influence brain morphology and physiology during both development and aging. Here we apply a machine learning data to examine the influence of sex on brain aging in vivo. These

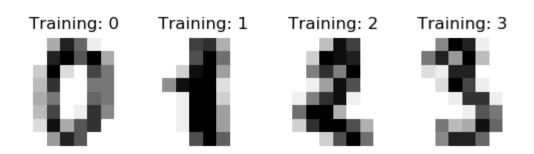
- 1. Collect PET data from 200+
- 2. Train on a RandomForest Regression Model
- 3. Predict age from PET (Brain Age)
- 4. Conclusion:
 - ✓ Find way to represent Brain Age
 - ✓ Women's brain aging slower



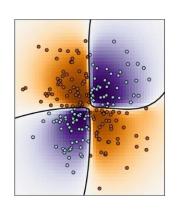
"Ten-fold cross-validation demonstrates that the predicted age based on this algorithm—defined as metabolic brain age—closely matches the actual chronological age of the participants (Pearson's r = 0.88-0.90 over 10 runs)"

PNAS paper on RandomForest & PET

- Not a traditional experiment
 - -Data driven, no hypothesis or manipulation
- Nor a traditional modeling
 - -Unknown 'HOW' and 'WHAT'
- Yet if strong enough … ?



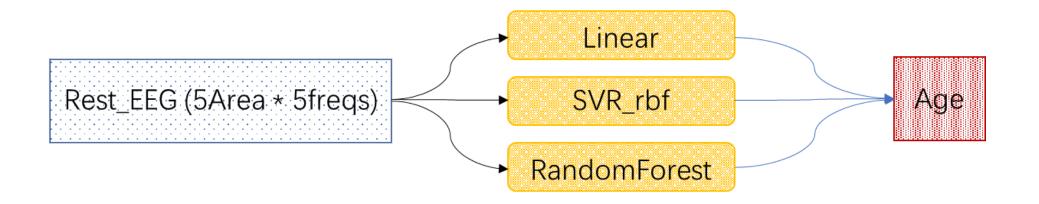




Blueprint

Setting principles in during constructing and running

Constructing: Features—Models—Target



Features – Models – Target

- Features : sets of EEG/ERP data
- Models : regression models
- Target : questionnaire result

-Features

• 16 sets of features

Group	Feature Sets	Length	Contains
Pain_EEG	pain_eeg_norm	400	Pain(2) * Pic_gender(2) * TimeWindow(4) * Freq(5) * Channels(5)
	pain_eeg_norm_Pain_	200	
	pain_eeg_norm_Neutral_	200	
	pain_eeg_orig	400	
	pain_eeg_orig_Pain_	200	
	pain_eeg_orig_Neutral_	200	
	pain_erp_amplitude_norm	80	Pain(2) * Pic_gender(2) * TimeWindow(4) * Channels(5)
	pain_erp_amplitude_norm_Pain_	40	
Pain_ERP_amplitude	pain_erp_amplitude_norm_Neutral_	40	
Pain_ERP_amplitude	pain_erp_amplitude_orig	80	
	pain_erp_amplitude_orig_Pain_	40	
	pain_erp_amplitude_orig_Neutral_	40	
Pain_ERP_peak	pain_erp_peak	16	Pain(2) * Pic_gender(2) * TimeWindow(4)
Rest_EEG	rest_norm	25	Freq(5) * Channels(5)
	rest_orig	25	
*Test	test_X	50	25 informative + 25 noise

-Models

• 12 regression models

```
def model set 2():
   model dict = dict()
   model dict['linear'] = get linear()
   model dict['riged'] = get riged(alpha=0.1)
   model dict['lars'] = get lars(alpha=0.5)
   model dict['bayesian'] = get bayesian()
   model dict['svr rbf'] = get svm(C=10.0, gamma='scale')
   model dict['svr linear'] = get svm(kernel='linear', C=10.0, gamma='scale')
   model dict['svr poly'] = get svm(kernel='poly', C=10.0, gamma='scale')
   model dict['gaussian'] = get gaussian(alpha=0.001)
   model dict['kneighbors'] = get kneighbors(n neighbors=5)
   model_dict['random_forest'] = get_random_forest(max_depth=50, n_estimators=5000)
   model_dict['gradient_trees'] = get_gradient_trees(max_depth=5, n_estimators=1000)
   model dict['neural network'] = get neural network(hidden layer sizes=(100, 50,))
   return model dict
```

-Target

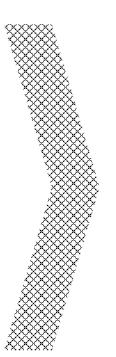
• 14 targets

Group	Target						
Age	age						
Race	race_identity						
Face recognition	face_recognition						
Day Dream	day_dream						
	IRI_FS						
IRI	IRI_EC						
IKI	IRI_PT						
	IRI_PD						
Self	Interdependent						
Sell	Independent						
Altruism	altruism						
Anxiety	anxiety						
Depression	depression						
*Test	Test_Y						

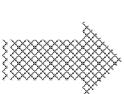
Constructing: Features-Models-Target

• 16 features * 12 models * 14 targets = 2688 train & test

Feature Sets
pain_eeg_norm
pain_eeg_norm_Pain_
pain_eeg_norm_Neutral_
pain_eeg_orig
pain_eeg_orig_Pain_
pain_eeg_orig_Neutral_
pain_erp_amplitude_norm
pain_erp_amplitude_norm_Pain_
pain_erp_amplitude_norm_Neutral_
pain_erp_amplitude_orig
pain_erp_amplitude_orig_Pain_
pain_erp_amplitude_orig_Neutral_
pain_erp_peak
rest_norm
rest_orig
test_X

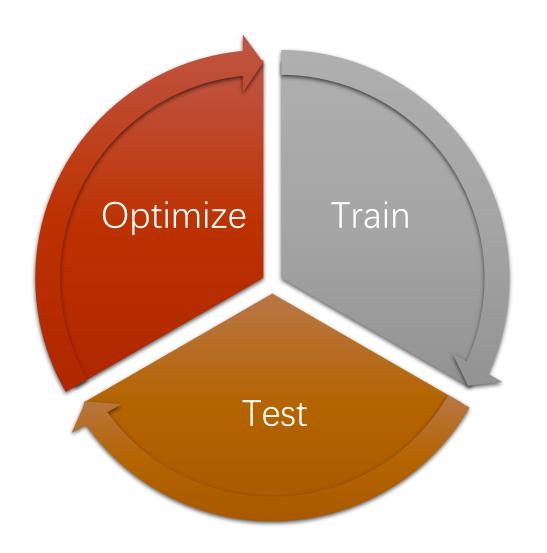


Models
linear
riged
lars
bayesian
svr_rbf
svr_linear
svr_poly
gaussian
kneighbors
random_forest
gradient_trees
neural network



Target age race_identity face_recognition day_dream IRI_FS IRI_EC IRI PT IRI PD Interdependent Independent altruism anxiety depression Test Y

Running: Train-Test-Optimizing



- Test: 10%-fold, 10 run times
- How to optimize
 - Enhance data
 - Better preprocessing
 - Enhance Models
 - Tuning hyper-parameters
 - Speed up



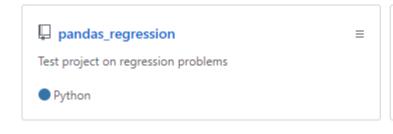
Implementation

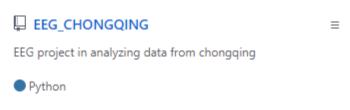
Preprocessing data, building models, testing, tuning parameters as well as self-checking

Two projects on Github

- EEG_CHONGQING
- Goal : EEG/ERP data pre-processing
- Packages
 - mne : Read cnt, ICA, Morlet, Epoch, Peak ···
 - numpy: custom (avg across channel area)
- https://github.com/MoonKuma/EEG_CHONGQING

- pandas_regression
- Goal : structuring and training regression models
- Packages
 - pandas: store and preprocess data(rating questionnaire, merging)
 - sklearn : machine learning models
- https://github.com/MoonKuma/pandas_regression







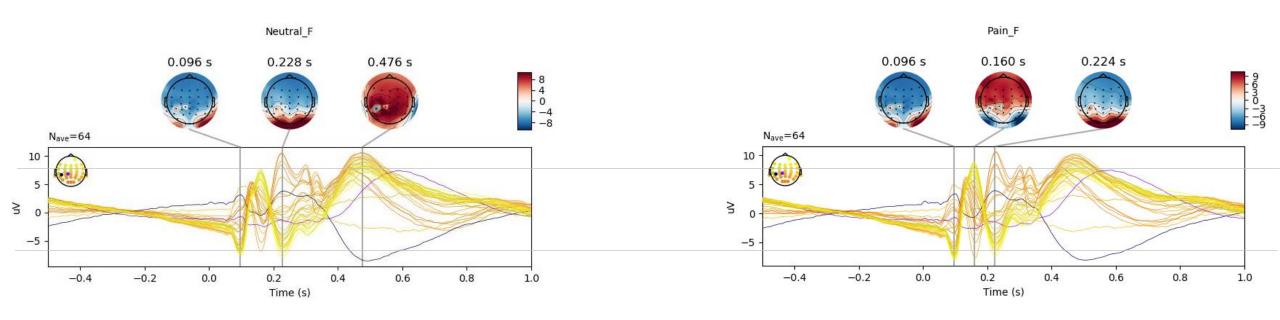
EEG/ERP preprocessing

- Raw -> Power/Amplitude Epochs -> Time Window averaged
 - https://github.com/MoonKuma/EEG_CHONGQING/blob/master/eeg_pre_processing/preprocessing_pipeline.md
- Common procedures

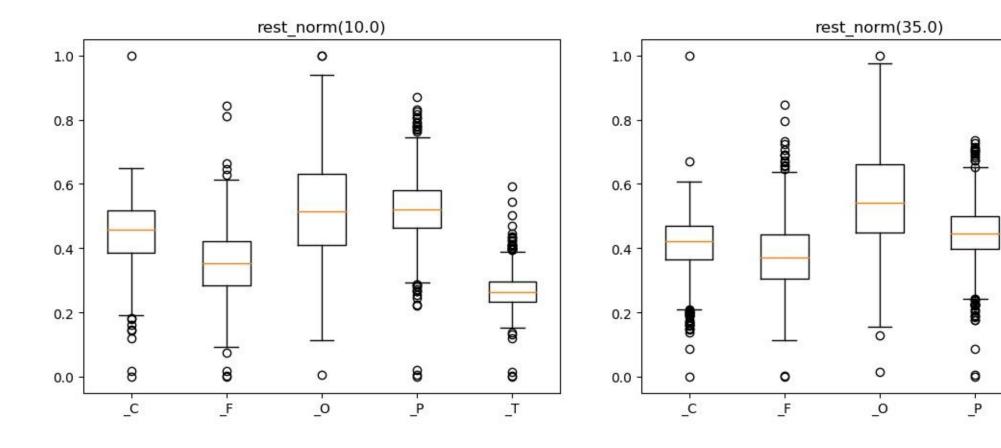
Load, down-sample, Filter, ICA, Baseline, Epoch, Morlet, Average across time-window

- Custom procedures
 - Events of resting states
 - 2s time window randomly separated in each 4s
 - Normalize (L2)
 - Average across channel areas
 - [F/C/T/P/O]

Preprocessed

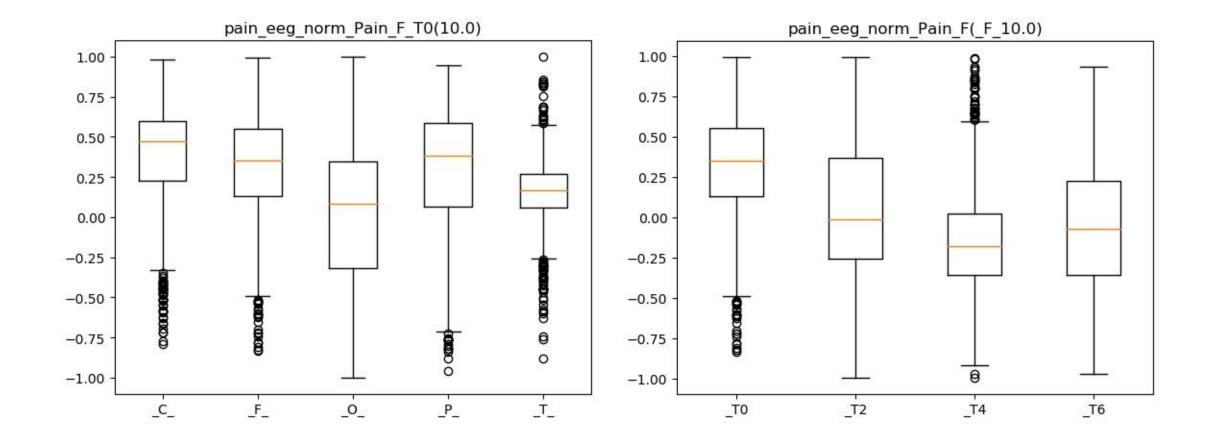


Rest EEG across channels/freqs

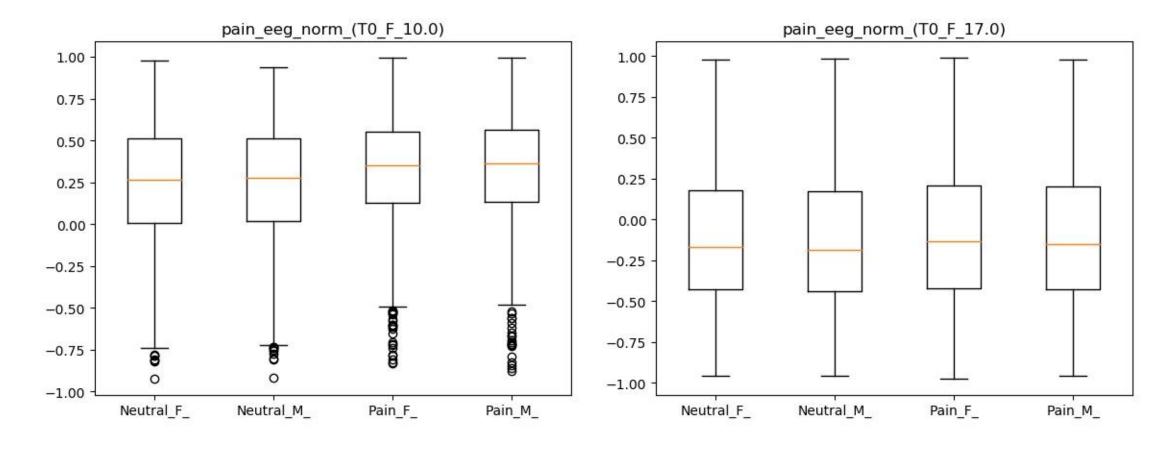


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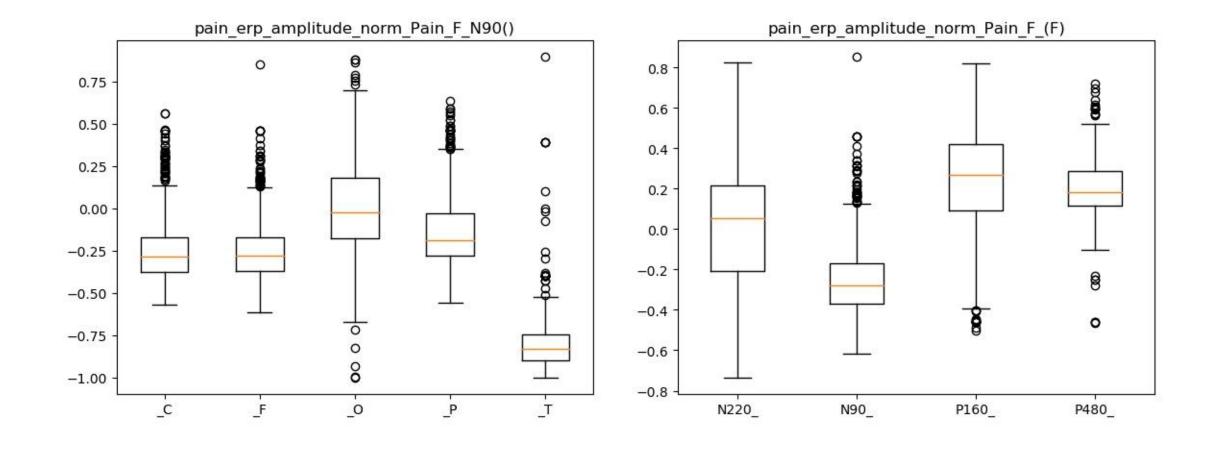
Pain EEG across channels/time window



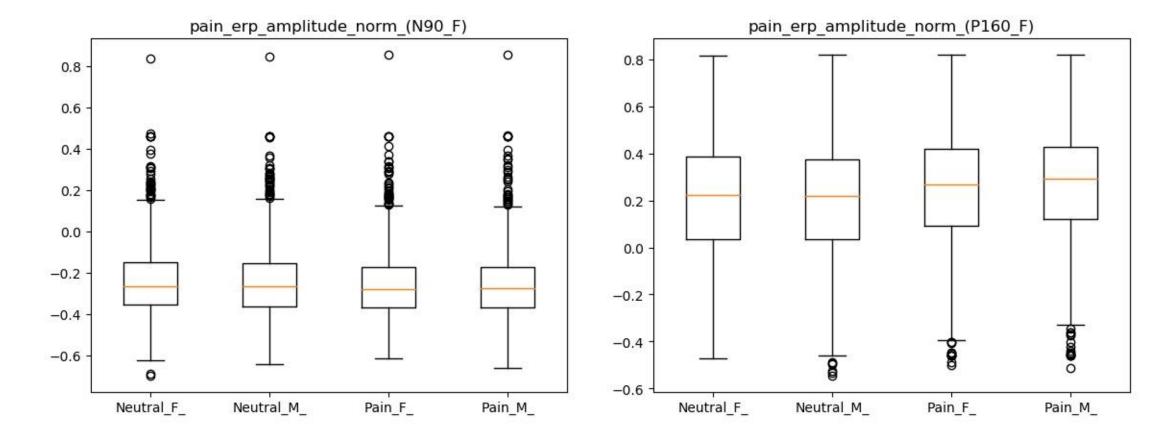
• Pain EEG across conditions (Pain vs. Neutral, Male vs. Female)



Pain ERP across channels/time window



• Pain ERP across conditions (Pain vs. Neutral, Male vs. Female)



Result of model sets

Model set 1

```
def model set 1():
   model dict = dict()
   model dict['linear'] = get linear()
   model dict['riged'] = get riged()
   model dict['lars'] = get lars()
   model dict['bayesian'] = get bayesian()
   model_dict['svr_rbf'] = get_svm()
   model dict['svr linear'] = get svm(kernel='linear')
   model dict['svr poly'] = get svm(kernel='poly')
   model dict['gaussian'] = get gaussian()
   model dict['kneighbors'] = get kneighbors(n neighbors=10)
   model dict['random forest'] = get random forest(max depth=10, n estimators=1000)
   model dict['gradient trees'] = get gradient trees(max depth=10, n estimators=1000)
   model dict['neural network'] = get neural network(hidden layer sizes=(50, 25, 10))
   return model dict
```

```
# test>0.5: o
# test>0.1: +
# train>0.5 and test<0.1: *
# train<0.5 : -
```

	age		face_recognitio n	day_drea m	IRI_FS	IRI_EC	IRI_PT	IRI_PD	Interdepende nt	Independe nt	altruism	anxiety	depressio n	test_Y
pain_eeg_norm	-***- **	-*** 	-***-*	-***- 	-** *	-** *	-***- **	-***- **	-**	-*** 	-** *	-** *	-***- 	-***
pain_eeg_norm_Pain_	-** *	-*** 	-**	-***- 	-** *	-** *	-** *	-** *	-**	-*** 	-** *	-** *	-***- 	-***
pain_eeg_norm_Neutral_	-** *	-*** 	-**	-***- 	-** *	-** *	-** *	-** *	-**	-*** 	-** *	-** *	-***- 	-***
pain_eeg_orig			*										*	
pain_eeg_orig_Pain_														
pain_eeg_orig_Neutral_														
pain_erp_amplitude_norm	-** *	-***	-**	-***-	-** *	-** *	-** *	-** *	-**	-***	-** *	-** *	-***-	-***
pain_erp_amplitude_norm_Pain_	-** *	-***	-**	-***-	-** *	-** *	-** *	-** *	-**	-**	-** *	-** *	-***-	-***
pain_erp_amplitude_norm_Neut ral_	-** *	-***	-**	-***-	-** *	-** *	-** *	-**	-**	-***	-** *	-**	-***-	-***
pain_erp_amplitude_orig	*	*	*	*	*	*	*	*	*	*	*	*	*	*
pain_erp_amplitude_orig_Pain_	*	*	*	*	*	*	*	*	*	*	*	*	*	*
pain_erp_amplitude_orig_Neutra	*	*	*	*	*	*	*	*	*	*	*	*	*	*
- pain_erp_peak	-** *	-***	-**	-***-	-** *	-** *	-** *	-** *	-**	-***	-** *	-** *	-***-	-***
rest_norm	-**	-***	-**	-***-	-**	-** *	-**		-**	-***	-**	-**	-***-	-***
rest_orig														
test_X	-**	-***	-**	-***-	-**	-**	-**	-** *	-**	-***	-**	-**	-***-	0*++-0-

['bayesian', 'gaussian', 'gradient_trees', 'kneighbors', 'lars', 'linear', 'neural_network', 'random_forest', 'riged', 'svr_linear', 'svr_poly', 'svr_rbf']

Result of model sets

Model set 2 (More penalty)

```
def model set 2():
   model dict = dict()
   model dict['linear'] = get linear()
   model dict['riged'] = get riged(alpha=0.1)
   model dict['lars'] = get lars(alpha=0.5)
   model dict['bayesian'] = get bayesian()
   model dict['svr rbf'] = get svm(C=10.0, gamma='scale')
   model dict['svr linear'] = get svm(kernel='linear', C=10.0, gamma='scale')
   model dict['svr poly'] = get svm(kernel='poly', C=10.0, gamma='scale')
   model dict['gaussian'] = get gaussian(alpha=0.001)
   model dict['kneighbors'] = get kneighbors(n neighbors=5)
   model dict['random forest'] = get random forest(max depth=50, n estimators=5000)
   model_dict['gradient_trees'] = get_gradient_trees(max_depth=5, n_estimators=1000)
   model dict['neural network'] = get neural network(hidden layer sizes=(100, 50,))
   return model dict
```

	age	race_identit y	face_recognition	day_drea m	IRI_FS	IRI_EC	IRI_PT	IRI_PD	Interdepende nt	Independe nt	altruism	anxiety	depressio n	test_Y
pain_eeg_norm	-***- **	-*** 	-***-**	-***- 	-** *		-***- **	-***- **	-**	-*** 	-** *	-** **	-***- 	-*****-
pain_eeg_norm_Pain_	-** *	-*** 	-**	-***- 	-** *	-** *	-** *	-** *	-**	-*** 	-** *	-** *	-***- 	-****
pain_eeg_norm_Neutral_	-** *	-*** 	-**	-***- 	-** *	-** *	-** *	-** *	-**	-*** 	-** *		-***- 	-****
pain_eeg_orig			*							*			*	*
pain_eeg_orig_Pain_														
pain_eeg_orig_Neutral_														
pain_erp_amplitude_norm	-** *	-***	-**	-***- 	-** *	-** *	-** *	-** *	-**	-*** 	-** *	-** *	-***- 	-***
pain_erp_amplitude_norm_Pain_	-**	-***	-**	-***- 	-** *	-** *	-** *	-** *	-**	-*** 	-** *	-** *	-***-	-***
pain_erp_amplitude_norm_Neut ral	-** *	-***	-**	-***- 	-** *	-** *	-** *	-** *	-**	-*** 	-** *	-** *	-***-	-***
pain_erp_amplitude_orig	* *	**	*	**- 	* *	* *	* *	* *	*	**		* *	**-	**
pain_erp_amplitude_orig_Pain_	* *	**	**	**- 	* *	* *	* *	* *	*	**	* *		**-	**
pain_erp_amplitude_orig_Neutra	*	**	**	**-	* *	* *	* *	* *	*	**	* *	* *	**-	**
pain_erp_peak	* *	**	*	**-	* *	* *	* *	* *	*	**	* *	* *	**-	**
rest_norm	* *	**	**	**-	* *	* *	* *	* *	*	**	* *	* *	**-	**
rest_orig														
test_X	-** *	-***	-**	-***-	-** *	-** *	-** *	-** *	-**	-***	-** *		-***-	0*0+-0-
['havesian' 'daussian' 'dra	dient tr	'ees' 'kneid	nhhore' 'lare'	'lingar' 'r	naural r	natwork	' 'rando	m fore	ct' 'riged' 'ex	ır lingar' '	syr nol	ı' 'cvr r	hf'l	

['bayesian', 'gaussian', 'gradient_trees', 'kneighbors', 'lars', 'linear', 'neural_network', 'random_forest', 'riged', 'svr_linear', 'svr_poly', 'svr_rbf']

Result of model sets

Model set 3 (More complicate, still running after 20 hours)

```
def model_set_3():
    model_dict = dict()
    model_dict['linear'] = get_linear()
    model_dict['riged'] = get_riged(alpha=0.1)
    model_dict['gaussian'] = get_gaussian(alpha=0.01)
    model_dict['kneighbors'] = get_kneighbors(n_neighbors=20)
    model_dict['random_forest'] = get_random_forest(max_depth=None, n_estimators=10000)
    model_dict['gradient_trees'] = get_gradient_trees(max_depth=200, n_estimators=10000)
    return model_dict
```

For future optimization

- Data: maybe remove outliers
- Models:
 - Squeeze down feature set size
 - Regression -> classification
 - Hyper-parameters searching