Appendix A. Time series extraction

In order to extract time series from overlapping brain maps, we use an ordinary least square approach (**OLS**). Let $\mathbf{Y} \in \mathbb{R}^{n \times p}$ be the original subject signals of p voxels over n temporal scans and $\mathbf{V} \in \mathbb{R}^{k \times p}$ the atlas of k maps containing p voxels. We estimate $\mathbf{U} \in \mathbb{R}^{n \times k}$, the set of time series proper to each region, using an **OLS**:

$$\hat{\mathbf{U}} = \arg\min_{\mathbf{U}} \|\mathbf{Y} - \mathbf{U}\mathbf{V}\|$$

In order to remove the confounds, we orthogonalize our signals with regards to them. We do this by removing the the signals projected on an orthonormal basis of the confounds. Let $\mathbf{C} \in \mathbb{R}^{n \times c}$ be a matrix of c confounds:

$$\mathbf{C} = \mathbf{Q}\mathbf{R} \quad \text{with } \mathbf{Q} \text{ orthonormal}$$
$$\hat{\mathbf{Y}} = \mathbf{Y} - \mathbf{Q}\mathbf{Q}^{\mathsf{T}}\mathbf{Y}$$

Appendix B. Covariance matrix estimation

The empirical covariance matrix is not a good estimator when $n < p$. In particular, it can leads to the estimation of matrices that cannot be inverted. This problem can be avoided by using shrinkage, a method to pull the extreme values of the covariance matrix toward the central ones. It is done by finding the ℓ_2-penalized maximum likelihood estimator of the covariance matrix:

$$\Sigma_{\text{shrunk}} = (1 - \alpha)\hat{\Sigma} + \alpha \frac{\text{Tr}(\hat{\Sigma})}{p} Id$$

We use the Ledoit-Wolf approach [50] to set parameter α to minimize the Mean Square Error between the real and the estimated covariance matrix.

Appendix C. Classifiers

Linear classifiers try to find an hyperplane splitting the sample in the input space in order to classify them into two categories.

*Support Vector Classification **SVC***

SVC aims at maximizing the margin, *i. e.* the distance to the closest training sample and the hyperplane. We use the classical squared hinge loss and thus minimize:

$$\min_{\mathbf{w}} \frac{1}{2}|\mathbf{w}|_p + C\sum_{i=1}^{n} \|\mathbf{y}_i - \mathbf{w}^{\mathsf{T}}\mathbf{x}_i\|_2^2$$

With $\mathbf{w} \in \mathbb{R}^n$, $\mathbf{x} \in \mathbb{R}^{n \times m}$, and $\mathbf{y} \in \mathbb{R}^m$. In our case, n, the number of features, is the number of connections between pairs of brain regions and m, the number of samples, is the number of subjects. We explore the sparse regularization ℓ_1 and ℓ_2-penalized SVC (resp. $p = 1$ and $p = 2$). We use the implementation of scikit-learn [55] that relies on the implementation provided by LibLinear [77].

Ridge classifier

Ridge regression can be used in the context of classification by attributing binary values to each of the classes (typically -1 and 1). Classifying an sample boils down to looking at the sign of the prediction of the regressor.

The Ridge regression minimizes the square distance to the hyperplane, like an ordinary least squares, but it adds an ℓ_2 penalization on the weights in order to reward coefficients close to 0 and thus obtain the *smallest* possible model. This prevents colinear feature to skew the coefficients of the model. The minimized function is:

$$\min_{\mathbf{w}} \|\mathbf{y} - \mathbf{w}^{\mathsf{T}}\mathbf{x}\|_2 + \|\mathbf{w}\|_2$$

We use the implementation of scikit-learn [55].

Appendix D. Effect of movements

Participant's movements during fMRI acquisition is known to induce spurious correlations in the connectome estimation. In our particular case, we expect healthy individuals and ASD ones to exhibit different movement patterns because of the behavioral symptoms of the latter.

In our study, we use standard methods to remove the effect of movement as much as possible. We also performed an analysis to measure the amount of information contained in the movement patterns and ensure that our predictions are not based on potential movement residuals.

Movement regression

In the experiments, during time series extraction (step 2), we regress out all possible confounding factors, which includes movement estimation. In order to quantify the information contained in the movements, we try predicting ASD diagnosis with and without movement regression. Figure A1 shows that no significant difference is observed with and without movement regression, which means that movement effect does not affect strongly our connectome estimation.

Movement-based prediction

Going further, we also perform the diagnosis directly based on movement estimations. Because movement parameters are time-series, it is not possible to use them directly as features in a prediction task. For this purpose, we extract temporal descriptors from these series. These descriptors are similar to the ones extracted in FSL FIX [78], a tool to identify noisy ICA components: coefficients of autoregressive models of several orders, kurtosis, skewness, entropy, difference between the mean and the median, and Fourier transform coefficients.

As for the prediction pipelines, we tried a wide range of strategies to predict from movement parameters. We extracted the descriptors on the movements, the gradient of the movements, the gradient squared, and the framewise

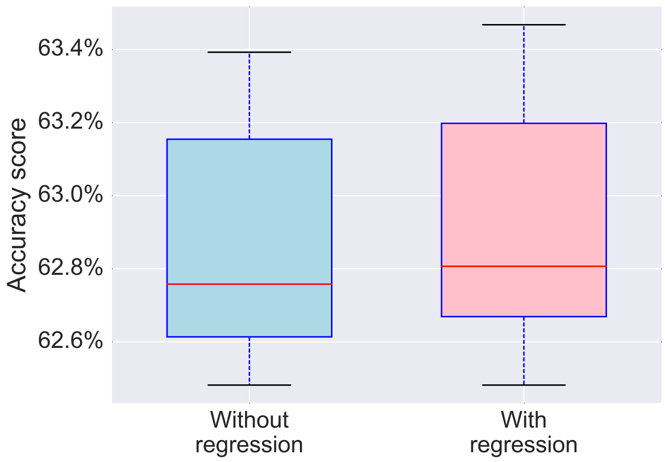


Figure A1: **Prediction accuracy scores with and without performing movement regression during time series extraction.** No significant difference is observed.

displacement. We tried several predictors (with and without feature extraction), logistic regression, SVC, Ridge classifier, Gaussian Naive Bayes and random forests.

We present the results obtained on the best prediction procedure. For each participant, 56 descriptors are extracted from the movement estimations and their gradient, and are used as features in an SVC for diagnosis. We observe that the scores obtained using movements are at chance level. Note that we see a trend already observed on prediction based on connectomes: The variance of prediction scores is much larger for inter-site prediction.

	Right handed males 9-18 yo			Biggest sites	All subjects
	3 sites				
Intra-site Accuracy	53.2% ±0.1%	53.9% ±0.6%	53.5% ±0.2%	53.0% ±0.2%	54.3% ±0.1%
Inter-site Accuracy		53.8% ±8.1%	54.3% ±8.3%	51.5% ±7.3%	52.8% ±8.2%

Table A1: **Prediction accuracy scores based on movements estimations.** Results are similar across folds but variance of inter-site prediction is larger.

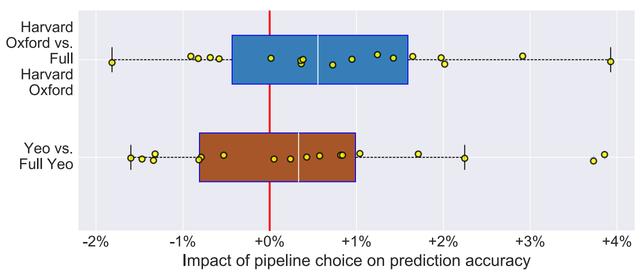


Figure A2: **Comparison of prediction results obtained using 84 regions extracted from Harvard Oxford and Yeo atlases against the set of all regions extracted from them (labelled as *full*).** Results obtained using 84 regions are better than full atlases. This is probably due to the fact that small regions can induce spurious correlations in the connectivity matrices.

Figure A3: **Classification accuracy scores using overlapping atlases and their non overlapping counterpart.** Point above the identity line support the idea that fuzzy overlapping maps are better at predicting behavioral variable than non-overlapping.

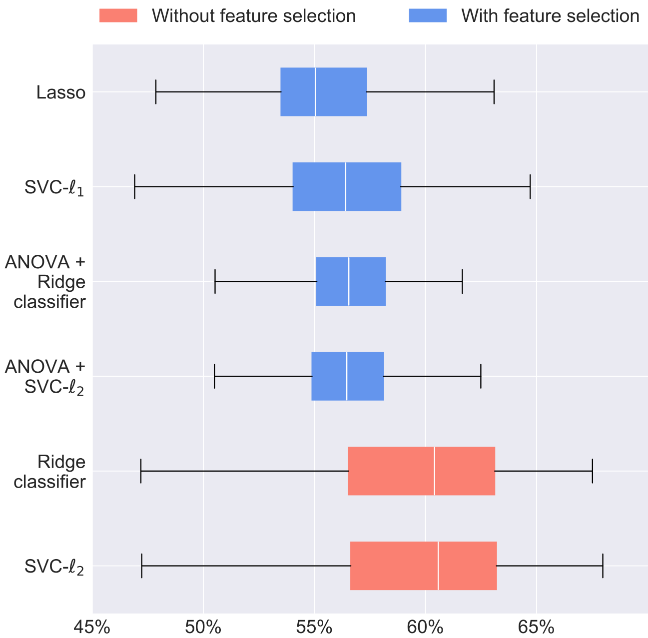


Figure A4: **Comparison of prediction results obtained using feature selection or sparse methods.** When selecting a reduced number of features, using either ANOVA to select 10% of the features, or sparsity inducing methods, we observe that the prediction accuracy drops compared to a classification using all features. This can be due to the fact that the connectivity matrices represent mixed features that should be handled together rather than seaprately. This may also be due to global effects in the connectivity: A global hypoconnectivity, as already observed in ASD patients, cannot be captured by ℓ_1 regularized classifiers.

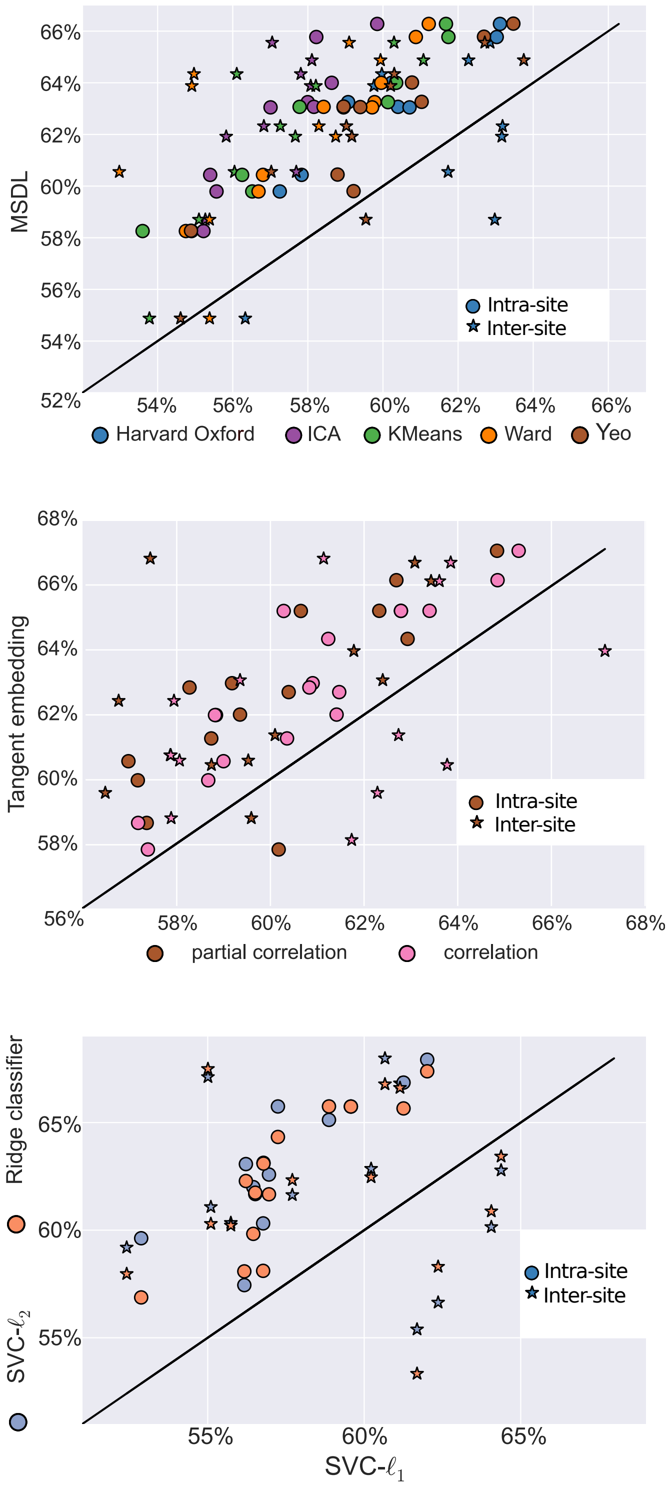


Figure A5: **Comparison of pipeline options.** Each plot compares the results of the best option against the other for each step. Points above the line means that the option show on y-axis is better than option on the x-axis. The 2 cross validation schemes are represented by circles and stars.

	All subjects		Biggest sites		Right-handed males		Right-hand males, 9-18		Right-hand males, 9-18, 3 sites	
Sites	ASD	TC	ASD	TC	ASD	TC	ASD	TC	ASD	TC
CALTECH	5	10								
CMU	6	5								
KKI	12	21	12	21	7	15	6	12		
LEUVEN_1	14	14	14	14	13	13	1	1		
LEUVEN_2	12	16	12	16	7	12	7	12		
MAX_MUN	19	27	19	27	16	25	5	3		
NYU	74	98	74	98	60	70	36	40	36	40
OHSU	12	13			10	13	9	11		
OLIN	14	14	14	14	8	11	7	7		
PITT	24	26	24	26	20	18	11	10		
SBL	12	14								
SDSU	8	19	8	19	7	10	7	10		
STANFORD	12	13			8	9	7	6		
TRINITY	19	25	19	25	18	24	12	14		
UCLA_1	37	27	37	27	29	24	28	24	28	24
UCLA_2	11	10	11	10	9	8	9	8	9	8
UM_1	34	52	34	52	23	34	22	30	22	30
UM_2	13	21	13	21	12	19	12	17	12	17
USM	43	24	43	24	37	22	12	7		
YALE	22	19	22	19	8	10	7	10		
Total	403	468	356	413	292	337	198	222	107	119

Table A2: Count of subjects per site and per subsamples.

Cross validation	Atlas estimator	Right handed males 9-18 yo, 3 sites	Right handed males 9-18 yo	Right handed males	Biggest sites	All subjects
Intra-site	MSDL	**66.6% ± 5.4%**	**65.8% ± 5.9%**	**65.7% ± 4.9%**	**67.9% ± 1.9%**	**66.9% ± 2.7%**
	Yeo	60.9% ± 7.5%	62.3% ± 3.6%	64.7% ± 3.1%	64.7% ± 2.9%	66.9% ± 3.0%
	Harvard Oxford	63.6% ± 2.7%	62.1% ± 4.6%	64.8% ± 5.1%	64.8% ± 2.5%	66.4% ± 2.7%
	ICA	61.3% ± 8.7%	62.3% ± 3.0%	61.6% ± 4.3%	65.2% ± 3.1%	62.0% ± 3.4%
	K-Means	62.6% ± 5.9%	61.4% ± 5.4%	61.5% ± 3.0%	61.3% ± 3.4%	65.1% ± 1.8%
	Ward	63.2% ± 6.3%	60.1% ± 6.0%	62.2% ± 4.9%	64.6% ± 2.7%	63.7% ± 3.4%
Inter-site	MSDL		68.3% ± 7.6%	63.4% ± 6.3%	**68.7% ± 9.3%**	**66.8% ± 5.4%**
	Yeo		**69.7% ± 8.9%**	64.5% ± 10.3%	61.4% ± 7.9%	61.3% ± 7.2%
	Harvard Oxford		68.1% ± 9.0%	**65.1% ± 5.8%**	62.4% ± 5.4%	63.6% ± 6.2%
	ICA		63.1% ± 9.9%	62.5% ± 7.8%	65.0% ± 4.8%	60.9% ± 5.2%
	K-Means		62.8% ± 13.9%	61.5% ± 8.1%	61.9% ± 10.1%	60.3% ± 4.8%
	Ward		62.4% ± 11.7%	59.8% ± 6.9%	63.4% ± 5.4%	63.1% ± 4.0%

Table A3: **Average accuracy scores (along with their standard deviations) for top performing pipelines**. This table summarizes the scores for pipelines with best prediction accuracy for each atlas and subset using intra-site or inter-site prediction. Best results are shown in bold.

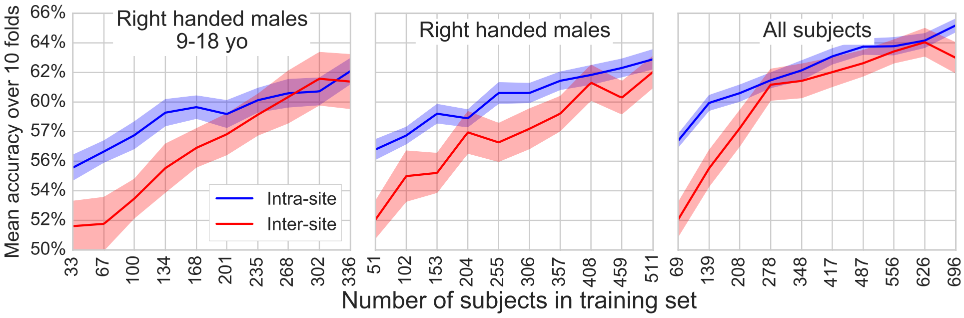
Cross validation	Atlas estimator	Right handed males 9-18 yo, 3 sites	Right handed males 9-18 yo	Right handed males	Biggest sites	All subjects
Intra-site	MSDL	**73.6% ± 11.7%**	**76.5% ± 25.1%**	62.4% ± 21.3%	**59.3% ± 8.0%**	**61.3% ± 4.8%**
	Yeo	68.2% ± 36.5%	63.0% ± 20.2%	58.5% ± 4.7%	59.0% ± 5.1%	59.6% ± 5.6%
	Harvard Oxford	67.7% ± 23.3%	61.4% ± 10.8%	59.5% ± 5.3%	57.4% ± 7.8%	59.5% ± 6.0%
	ICA	69.1% ± 12.1%	65.7% ± 24.5%	**64.4% ± 7.9%**	57.3% ± 4.2%	**61.3% ± 6.5%**
	K-Means	69.1% ± 12.3%	68.9% ± 22.7%	61.4% ± 5.3%	53.3% ± 5.9%	60.4% ± 6.6%
	Ward	66.4% ± 20.9%	63.2% ± 21.4%	62.7% ± 5.8%	53.3% ± 4.9%	59.8% ± 5.9%
Inter-site	MSDL		**72.7% ± 19.0%**	67.5% ± 10.8%	**67.9% ± 9.0%**	66.6% ± 14.7%
	Yeo		65.4% ± 13.7%	67.1% ± 14.7%	57.2% ± 9.4%	59.1% ± 8.8%
	Harvard Oxford		71.9% ± 22.5%	66.7% ± 21.2%	60.7% ± 12.1%	64.2% ± 9.0%
	ICA		69.9% ± 17.1%	65.8% ± 13.0%	63.4% ± 12.2%	**68.9% ± 6.7%**
	K-Means		69.7% ± 13.2%	**67.7% ± 13.7%**	60.3% ± 15.2%	67.7% ± 6.2%
	Ward		66.0% ± 12.1%	63.3% ± 16.9%	59.5% ± 9.3%	65.4% ± 9.7%

Table A4: **Average specificity scores (along with their standard deviations) for top performing pipelines**. This table summarizes the scores for pipelines with best prediction accuracy for each atlas and subset using intra-site or inter-site prediction. Best results are shown in bold.

Cross validation	Atlas estimator	Right handed males 9-18 yo, 3 sites	Right handed males 9-18 yo	Right handed males	Biggest sites	All subjects
Intra-site	MSDL	**85.2%** ± **14.6%**	**86.0%** ± **12.9%**	88.1% ± 12.6%	**84.9%** ± **11.7%**	**90.9%** ± **7.5%**
	Yeo	82.0% ± 13.2%	82.1% ± 8.4%	84.3% ± 12.6%	81.1% ± 6.1%	79.7% ± 3.4%
	Harvard Oxford	83.6% ± 14.3%	79.1% ± 20.4%	85.9% ± 10.6%	84.4% ± 3.0%	82.3% ± 2.7%
	ICA	80.4% ± 16.4%	77.7% ± 11.8%	**88.4%** ± **8.2%**	81.5% ± 8.2%	85.1% ± 4.4%
	K-Means	74.0% ± 13.1%	78.8% ± 20.3%	79.4% ± 19.0%	83.2% ± 5.7%	80.0% ± 12.2%
	Ward	78.0% ± 11.0%	77.0% ± 11.3%	80.0% ± 16.2%	80.4% ± 3.6%	80.4% ± 4.3%
Inter-site	MSDL		**84.2%** ± **10.5%**	**85.4%** ± **12.5%**	**85.5%** ± **13.6%**	**100.0%** ± **0.0%**
	Yeo		80.4% ± 12.3%	81.5% ± 16.0%	76.5% ± 16.3%	80.0% ± 15.1%
	Harvard Oxford		69.7% ± 16.5%	71.9% ± 10.9%	73.3% ± 13.6%	88.7% ± 18.9%
	ICA		71.2% ± 16.2%	72.5% ± 7.6%	75.5% ± 12.9%	93.1% ± 15.0%
	K-Means		75.4% ± 18.3%	67.2% ± 14.3%	68.4% ± 16.8%	94.3% ± 18.1%
	Ward		70.3% ± 17.0%	63.2% ± 11.8%	74.1% ± 10.8%	82.6% ± 22.9%

Table A5: **Average sensitivity scores (along with their standard deviations) for top performing pipelines**. This table summarizes the scores for pipelines with best prediction accuracy for each atlas and subset using intra-site or inter-site prediction. Best results are shown in bold.

Figure A6: **Learning curves.** Classification results obtained by varying the number of subjects in the training set while keeping a fixed testing set. The colored band represent the standard error of the prediction accuracy. A score increasing with the number of subjects, *i. e.* an increasing curve, indicates that the addition of new subjects brings information.



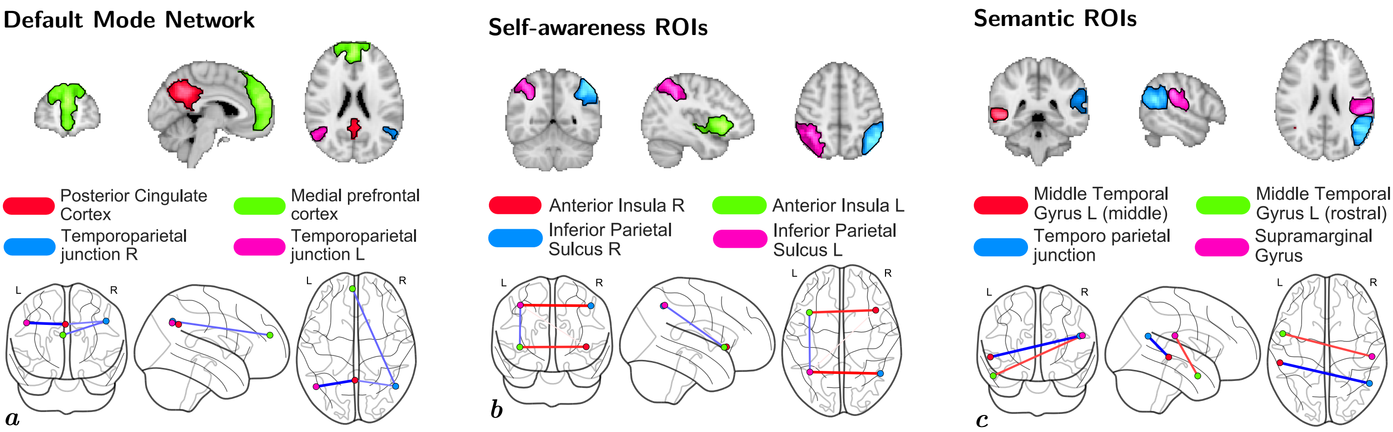
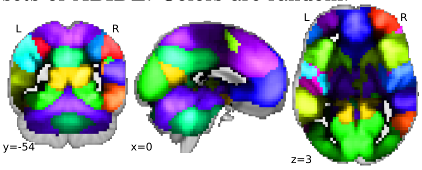
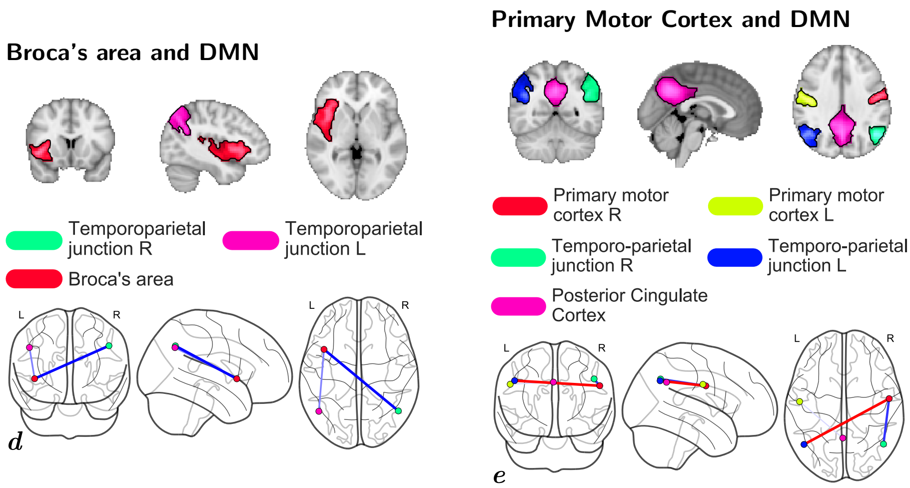


Figure A7: **Connections significantly non-zero in the predictive biomarkers distinguishing controls from ASD patients.** Red connections are stronger in controls and blue connections are stronger in ASD patients. Subfigures *a*, *b*, *c*, *d* and *e* reported intra-network difference. below is the consensus atlas extracted by selecting regions consistently extracted on 10 subsets of ABIDE. Colors are random.





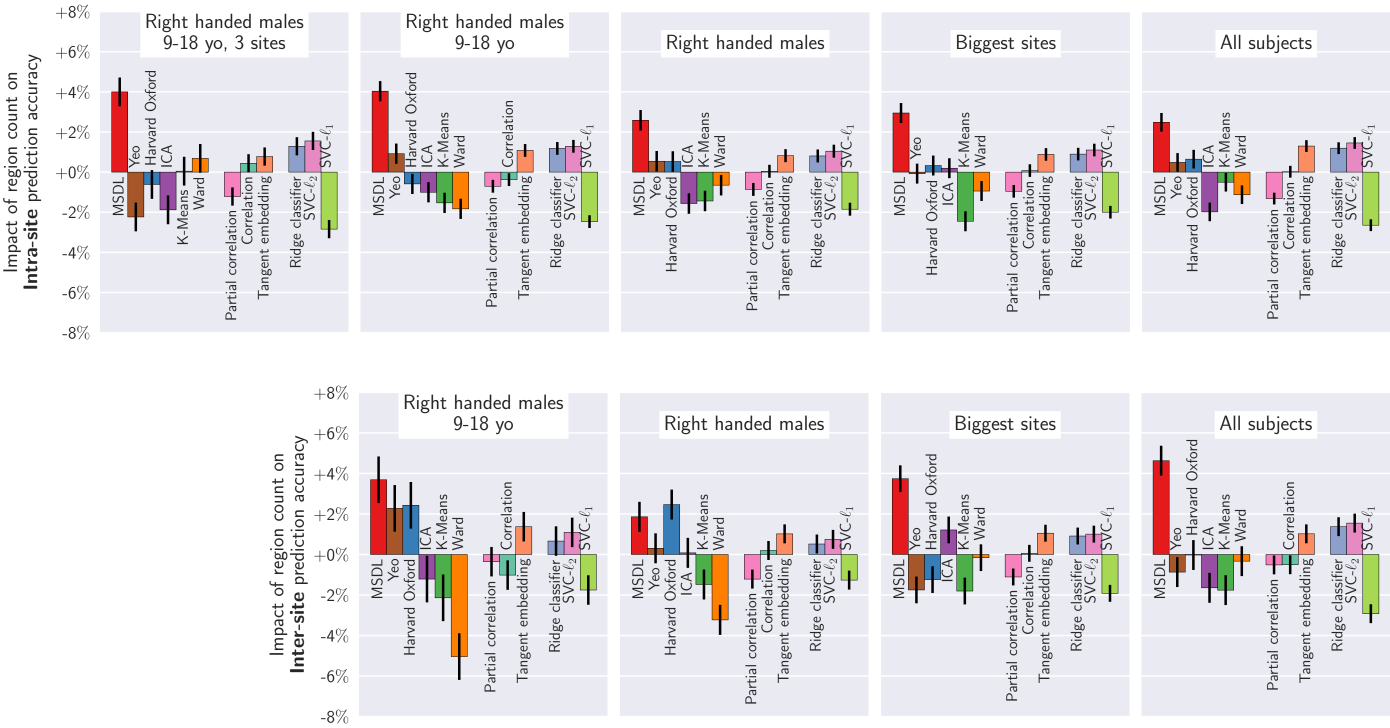
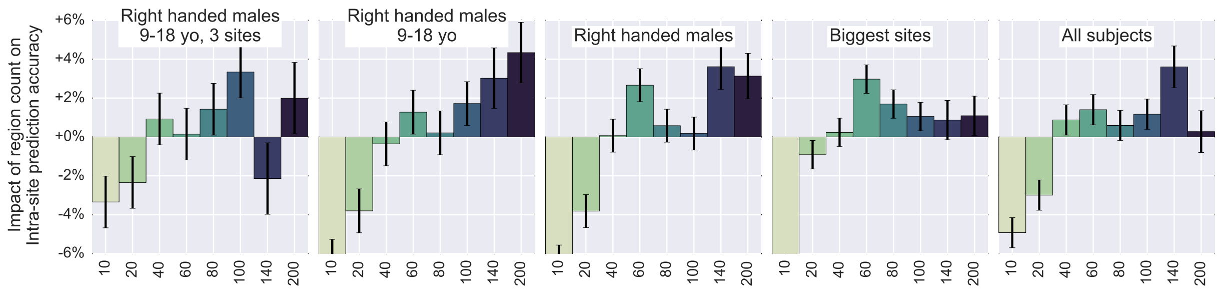


Figure A8: **Impact of pipeline steps on prediction.** Each plot represents the impact of each step of the pipeline for every subsets of ABIDE. In each figure, a block of bars represents a step of the pipeline (namely step 1, 3 and 4). Each bar represents the impact of the corresponding option on the prediction accuracy, relatively to the mean prediction. This effect is measured via a full-factorial ANOVA, analyzing the contribution of each step in a linear model. Each step of the pipeline is considered as a categorical variable. Error bars give the 95% confidence interval. MSDL atlas extraction method gives significantly better results while reference atlases are slightly better than the mean. Among all matrix types, tangent embedding is the best on all ABIDE subsets. Finally, l_2 regularized classifiers are better than l_1 regularized.



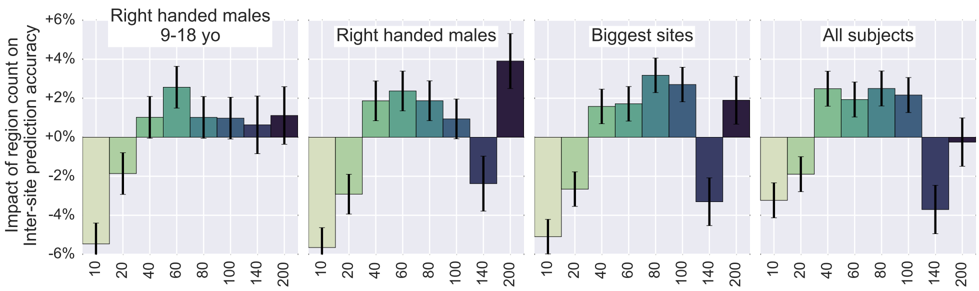


Figure A9: **Impact of region number on prediction**: each bar indicates the impact of the number of regions on the prediction accuracy relatively to the mean of the prediction. These values are coefficients in a linear model explaining the best classification scores as function of the number of regions. Error bars give the 95% confidence interval, computed by a full factorial ANOVA. Atlases containing more than 40 ROIs give better results in all settings.

ID	2	3	4	5
50003	●	●		
50004	●	●		
50005	●			
50006	●	●	●	
50007	●	●	●	
50008	●	●		
50010	●	●		
50011	●			
50012	●	●		
50013	●	●	●	
50014	●	●	●	
50015	●	●	●	
50016	●	●		
50020	●	●		
50022	●	●	●	
50023	●			
50024	●	●		
50025	●	●		
50026	●	●	●	
50027	●	●	●	
50028	●	●	●	
50030	●	●		
50031	●	●	●	
50032	●	●		
50033	●	●	●	
50034	●	●	●	
50035	●			
50036	●			
50037	●	●		
50038	●			
50039	●			
50040	●	●		
50041	●	●		
50042	●	●		
50043	●	●	●	
50044	●	●	●	
50045	●			
50046	●	●		
50047	●	●	●	
50048	●	●	●	
50049	●			
50050	●	●	●	
50051	●	●	●	
50052	●			
50053	●	●	●	
50054	●	●	●	
50056	●	●	●	
50057	●			
50059	●			
50060	●	●		
50102	●	●	●	
50103	●			
50104	●	●	●	
50105	●	●	●	
50106	●	●	●	
50107	●	●		
50109	●	●		
50111	●	●	●	
50112	●	●	●	
50113	●			
50114	●			
50115	●	●		
50116	●	●	●	
50117	●	●		
50118	●	●	●	
50119	●			
50121	●	●		
50123	●			
50124	●	●	●	
50125	●			
50127	●			
50128	●	●	●	
50129	●	●	●	
50130	●	●	●	
50131	●			
50132	●	●	●	
50134	●	●	●	
50135	●			
50142		●	●	
50143		●	●	
50144		●	●	
50145		●	●	
50146		●		
50147		●	●	
50148				
50149		●	●	
50150				
50152		●	●	
50153		●	●	
50156		●	●	
50157		●	●	
50158		●	●	
50159		●	●	
50160		●	●	
50161		●	●	
50162		●		
50163		●	●	
50164		●		
50167		●	●	
50168		●	●	
50169		●	●	
50170		●	●	
50171		●	●	
50182	●	●	●	
50183	●	●	●	
50184	●			
50186	●	●	●	
50187	●	●	●	
50188	●	●	●	
50189	●	●	●	
50190	●	●	●	
50193	●	●	●	
50194	●	●	●	
50195	●			
50196	●	●	●	
50198	●	●	●	
50199	●	●	●	
50200	●	●	●	
50201	●			
50202	●	●	●	
50203	●	●	●	
50204	●			
50205	●			
50206	●			
50208	●			
50210	●			
50213	●			
50214	●	●	●	
50215	●			
50217	●	●	●	
50232	●	●		
50233	●	●		
50234	●	●	●	
50236	●	●		
50237	●	●		
50239	●	●	●	
50240	●	●	●	
50241	●	●	●	
50243	●	●	●	
50245	●			
50247	●	●	●	
50248	●	●	●	
50249	●	●	●	
50250	●	●	●	
50251	●	●	●	
50252	●	●	●	
50253	●	●		
50254	●	●		
50255	●	●	●	
50257	●	●	●	
50259	●	●		
50260	●	●		
50261	●	●		
50262	●	●		
50263	●	●		
50264	●	●		
50265	●	●	●	
50266	●	●	●	
50267	●	●	●	
50268	●	●	●	
50269	●	●	●	
50270	●	●		
50271	●	●		
50272	●	●	●	●
50273	●	●	●	●
50274	●	●	●	●
50275	●	●	●	●
50276	●			
50278	●			
50282	●	●	●	●
50284	●			
50285	●			
50287	●	●	●	●
50289	●	●	●	●
50290	●	●	●	●
50291	●	●	●	●
50292	●	●	●	●
50293	●	●	●	●
50294	●	●	●	●
50295	●	●	●	●
50297	●	●	●	●
50298	●	●	●	●
50300	●			
50301	●	●	●	●
50302	●			
50304	●	●	●	●
50308	●			
50310	●	●	●	●
50312	●	●	●	●
50314	●	●	●	●
50315	●	●	●	●
50318	●			
50319	●			
50320	●	●		
50321	●			
50324	●	●	●	●
50325	●			
50327	●	●	●	●
50329	●	●	●	●
50330	●	●	●	●
50331	●	●	●	●
50332	●	●	●	●
50333	●	●	●	●
50334	●	●	●	●
50335	●	●	●	●
50336	●			
50337	●	●	●	●
50338	●			
50339	●	●	●	●
50340	●			
50341	●			
50342	●	●	●	●
50343	●			
50344	●	●		
50345	●	●	●	●
50346	●	●		
50347	●	●	●	●
50348	●			
50349	●	●		
50350	●	●	●	●
50351	●	●	●	●
50352	●	●	●	●
50353	●			
50354	●			
50355	●	●	●	●
50356	●			
50357	●			
50358	●	●	●	●
50359	●	●	●	●
50360	●	●	●	●
50361	●			
50362	●	●	●	●
50363	●	●	●	●
50364	●	●	●	●
50365	●	●	●	●
50366	●	●		
50367	●	●	●	●
50368	●	●	●	●
50369	●			
50370	●	●	●	●
50372	●	●	●	●
50373	●			
50374	●			
50375	●			
50376	●			
50377	●	●	●	●
50379	●			
50380	●			
50381	●	●	●	●
50382	●	●		
50383	●			
50385	●	●	●	●
50386	●	●	●	●
50387	●	●	●	●
50388	●	●		
50390	●	●	●	●
50391	●	●	●	●
50397	●	●	●	●
50399	●	●	●	●
50402	●	●	●	●
50403	●	●	●	●
50404	●	●	●	●
50405	●	●	●	●
50406	●	●	●	●
50407	●			
50408	●	●	●	●
50410	●	●	●	●
50411	●	●	●	●
50412	●	●	●	●
50413	●	●	●	●
50414	●			
50415	●	●	●	●
50416	●	●	●	●
50417	●	●	●	●
50418	●	●	●	●
50419	●	●	●	●
50421	●	●	●	●
50422	●	●	●	●
50424	●	●	●	●
50425	●	●	●	●
50426	●	●	●	●
50427	●	●	●	●
50428	●	●	●	●
50433	●	●		
50434	●	●		
50435	●	●	●	
50436	●	●	●	
50437	●	●	●	
50438	●	●	●	
50439	●	●		
50440	●	●		
50441	●	●		
50442	●	●		
50443	●	●	●	
50444	●	●		
50445	●	●		
50446	●	●		
50447	●	●	●	
50448	●			
50449	●	●		
50453	●			
50463	●	●		
50466	●	●		
50467	●	●		
50468	●	●		
50469	●	●		
50470	●	●	●	
50477	●	●		
50480	●	●		
50481	●			
50482	●	●		
50483	●	●		
50485	●	●		
50486	●	●	●	
50487	●	●		
50488	●	●		
50490	●	●		
50491	●	●		
50492	●	●		
50493	●	●		
50494	●			
50496	●	●		
50497	●	●		
50498	●	●		
50499	●	●		
50500	●	●	●	
50501	●	●	●	
50502	●	●		
50503	●	●		
50504	●	●	●	
50507	●	●		
50509	●			
50510	●	●	●	
50514	●	●		
50515	●	●	●	
50516	●	●	●	
50518	●			
50519	●	●	●	
50520	●			
50521	●	●		
50523	●	●	●	
50524	●	●	●	
50525	●	●		
50526	●	●		
50527	●	●		
50528	●	●	●	
50529	●	●		
50530	●	●		
50531	●			
50532	●	●	●	
50551	●	●	●	
50552	●	●	●	
50555	●			
50557	●			
50558	●			
50561	●	●	●	
50563	●			
50565	●			
50568	●	●	●	
50569	●			
50570	●	●	●	
50571	●	●	●	
50572	●			
50573	●	●	●	
50574	●	●	●	
50575	●	●	●	
50576	●			
50577	●			
50578	●	●	●	
50601	●	●	●	
50602	●	●	●	
50603	●			
50604	●			
50606	●			
50607	●			
50608	●	●	●	
50612	●	●	●	
50613	●	●	●	
50614	●			
50615	●			
50616	●	●	●	
50619	●			
50620	●			
50621	●			
50622	●	●	●	
50623	●			
50624	●			
50625	●	●		
50626	●			
50627	●			
50628	●			
50642				
50644				
50647				
50648				
50649				
50654				
50656				
50659				
50664				
50665				
50669				
50682	●	●		
50683	●	●		
50685	●	●		
50686	●	●		
50687	●	●		
50688	●	●		
50689	●	●		
50690	●	●		
50691	●			
50692	●	●		
50693	●	●		
50694	●	●		
50695	●	●		
50696	●			
50697	●	●		
50698	●	●		
50699	●	●		
50700	●	●		
50701	●	●	●	
50702	●	●	●	
50703	●	●		
50704	●	●		
50705	●	●		
50706	●	●		
50707	●	●		
50708	●	●		
50709	●	●		
50711	●	●		
50722	●			
50723	●			
50724	●	●	●	
50725	●	●	●	
50726	●	●	●	
50728	●	●	●	
50730	●			
50731	●	●	●	
50733	●	●	●	
50735	●			
50737	●	●	●	
50738	●	●	●	
50739	●	●	●	
50740	●	●	●	
50741	●	●	●	
50742	●	●	●	
50743	●			
50744	●			
50745	●	●	●	
50748	●	●	●	
50749	●			
50750	●			
50751	●	●	●	
50752	●	●	●	
50754	●	●	●	
50755	●	●	●	
50756	●	●	●	
50757	●			
50772	●	●	●	
50773	●	●	●	
50774	●	●	●	
50775	●	●	●	
50776	●	●	●	
50777	●	●		
50778	●			
50780	●			
50781	●	●	●	
50782	●	●	●	
50783	●			
50786	●	●		
50790	●			
50791	●			
50792	●			
50796	●			
50797	●	●	●	
50798	●			
50799	●	●	●	
50800	●			
50801	●	●	●	
50803	●	●		
50807	●	●	●	
50812	●			
50814	●	●		
50816	●	●	●	
50817	●	●	●	
50818	●	●	●	
50820	●			
50821	●	●	●	
50822	●	●	●	
50823	●	●	●	
50824	●	●	●	
50952	●			
50954	●			
50955	●			
50956	●			
50957	●			
50958	●			
50959	●			
50960	●			
50961	●			
50962	●			
50964	●	●	●	●
50965	●	●	●	●
50966	●	●	●	●
50967	●			
50968	●	●	●	●
50969	●	●		
50970	●	●		
50972	●	●	●	●
50973	●	●	●	●
50974	●	●	●	●
50976	●	●	●	●
50977	●			
50978	●			
50979	●	●	●	●
50981	●	●	●	●
50982	●	●	●	●
50983	●	●	●	●
50984	●	●	●	●
50985	●	●	●	●
50986	●	●		
50987	●	●		
50988	●	●	●	●
50989	●	●	●	●
50990	●	●	●	●
50991	●	●	●	●
50992	●	●	●	●
50993	●	●	●	●
50994	●	●	●	●
50995	●	●	●	●
50996	●	●	●	●
50997	●	●	●	●
50999	●	●	●	●
51000	●	●	●	●
51001	●	●	●	●
51002	●	●		
51003	●	●		
51006	●	●	●	●
51007	●	●	●	●
51008	●	●	●	●
51009	●	●	●	●
51010	●			
51011	●	●		
51012	●	●	●	●
51013	●	●		
51014	●	●	●	●
51015	●	●		
51016	●	●		
51017	●	●		
51018	●	●		
51019	●	●		
51020	●	●		
51021	●	●		
51023	●	●		
51024	●	●		
51025	●	●		
51026	●	●		
51027	●	●		
51028	●	●		
51029	●	●		
51030	●	●		
51032	●	●		
51033	●	●	●	●
51034	●	●	●	●
51035	●	●	●	●
51036	●			
51038	●			
51039	●			
51040	●			
51041	●			
51042	●			
51044	●			
51045	●			
51046	●			
51047	●			
51048	●			
51049	●			
51050	●			
51051	●			
51052	●			
51053	●			
51054	●			
51055	●			
51056	●			
51057	●			
51058	●			
51059	●			
51060	●			
51061	●			
51062	●			
51063	●			
51064	●	●		
51065	●	●	●	●
51066	●	●		
51067	●	●		
51068	●	●		
51069	●	●		
51070	●			
51072	●	●	●	●
51073	●	●	●	●
51074	●	●	●	●
51075	●	●	●	●
51076	●	●	●	●
51077	●	●	●	●
51078	●	●		
51079	●	●		
51080	●	●		
51081	●	●		
51082	●	●		
51083	●	●		
51084	●	●	●	●
51085	●	●	●	●
51086	●	●	●	●
51087	●	●	●	●
51088	●	●	●	●
51089	●	●	●	●
51090	●	●	●	●
51091	●			
51093	●	●	●	●
51094	●	●	●	●
51095	●	●	●	●
51096	●	●	●	●
51097	●	●	●	●
51098	●	●	●	●
51099	●	●	●	●
51100	●	●	●	●
51101	●	●	●	●
51102	●	●	●	●
51103	●	●	●	●
51104	●	●	●	●
51105	●	●	●	●
51106	●	●	●	●
51107	●	●	●	●
51109	●	●	●	●
51110	●	●	●	●
51111	●	●	●	●
51112	●	●		
51113	●	●		
51114	●	●		
51116	●	●		
51117	●	●		
51118	●	●		
51122	●	●	●	●
51123	●	●	●	●
51124	●	●	●	●
51126	●	●	●	●
51127	●	●	●	●
51128	●	●	●	●
51129	●	●	●	●
51130	●	●		
51131	●	●		
51132	●	●		
51133	●	●	●	
51134	●	●	●	
51135	●	●	●	
51136	●			
51137	●	●	●	
51138	●	●	●	
51139	●	●		
51140	●	●	●	
51141	●	●	●	
51142	●	●	●	
51146	●	●		
51147	●	●		
51148	●	●		
51149	●	●		
51150	●	●		
51151	●	●		
51152	●	●		
51153	●	●		
51154	●	●		
51155	●	●		
51156	●	●		
51159	●	●	●	●
51161		●	●	
51162				
51163		●	●	
51164				
51168		●	●	
51169		●	●	
51170				
51171				
51173		●		
51177		●	●	
51178		●	●	
51179		●	●	
51180				
51181		●	●	
51182		●	●	
51183		●		
51184				
51185		●		
51187		●		
51188				
51189		●	●	
51192				
51194		●	●	
51197		●	●	
51198		●	●	
51201	●	●	●	●
51202	●	●	●	●
51203	●			
51204	●	●	●	●
51205	●	●	●	●
51206	●	●	●	●
51207	●			
51208	●	●	●	●
51210	●	●	●	●
51211	●	●	●	●
51212	●	●	●	●
51214	●	●	●	●
51215	●			
51216	●	●	●	●
51217	●	●	●	●
51218	●	●	●	●
51219	●			
51220	●	●	●	●
51221	●			
51222	●	●	●	●
51223	●	●	●	●
51224	●	●	●	●
51225	●	●	●	●
51226	●			
51228	●			
51229	●	●	●	●
51230	●			
51231	●	●	●	●
51234	●	●	●	●
51235	●	●	●	●
51236	●	●	●	●
51237	●	●	●	●
51239	●	●	●	●
51240	●	●	●	●
51241	●	●	●	●
51248	●	●	●	●
51249	●	●		
51250	●	●	●	●
51251	●	●	●	●
51252	●	●	●	●
51253	●	●	●	●
51254	●	●	●	●
51255	●	●	●	●
51256	●	●	●	●
51257	●	●	●	●
51260	●	●	●	●
51261	●	●	●	●
51262	●	●	●	●
51264	●			
51265	●	●	●	●
51266	●	●	●	●
51267	●			
51268	●	●	●	●
51269	●	●	●	●
51271	●	●	●	●
51272	●	●	●	●
51273	●	●	●	●
51275	●	●	●	●
51276	●	●	●	●
51277	●	●	●	●
51278	●	●	●	●
51279	●			
51280	●	●	●	●
51281	●	●	●	●
51291	●	●	●	●
51292	●			
51293	●	●	●	●
51294	●	●	●	●
51295	●	●	●	●
51297	●	●	●	●
51298	●	●	●	●
51299	●	●	●	●
51300	●			
51301	●	●	●	●
51302	●	●	●	●
51303	●			
51304	●	●	●	●
51305	●			
51306	●	●	●	●
51307	●	●	●	●
51308	●	●	●	●
51309	●	●	●	●
51311	●	●	●	●
51313	●	●	●	●
51315	●	●	●	●
51318	●	●		
51319	●	●		
51320	●	●		
51321	●			
51322	●	●		
51323	●	●		
51325	●			
51326	●	●		
51327	●	●		
51328	●	●		
51329	●	●	●	
51330	●	●		
51331	●	●		
51332	●	●		
51333	●	●		
51334	●	●		
51335	●	●		
51336	●	●		
51338	●	●		
51339	●	●		
51340	●	●		
51341	●	●		
51342	●	●		
51343	●	●		
51344	●	●		
51345	●	●		
51346	●	●		
51347	●	●		
51349	●	●	●	
51350	●	●	●	
51351	●	●	●	
51354	●	●	●	
51356	●	●	●	
51357	●	●	●	
51359	●			
51360	●	●		
51361	●	●	●	
51362	●	●		
51363	●	●		
51364	●	●		
51365	●	●		
51369	●	●		
51370	●			
51373	●	●		
51461				
51463				
51464				
51465				
51473				
51477				
51479				
51480				
51481				
51482				
51484				
51487				
51488				
51491				
51493				
51556				
51557				
51558				
51559				
51560				
51562				
51563				
51564				
51565				
51566				
51567				
51568				
51569				
51570				
51572				
51573				
51574				
51576				
51577				
51578				
51579				
51580				
51582				
51583				
51584				
51585				
51606	●			

Table A6: **Subjects used in subsample #1.** Membership to other subsamples is indicated by bullets.