

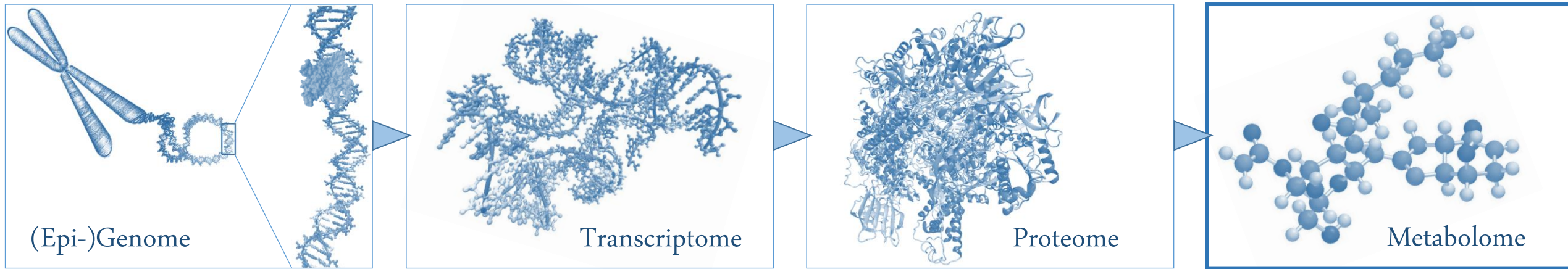
# Integrative Metabolomics: From Target Discovery to Disease Sub-Classification

## Alzheimer's Disease Metabolomics Consortium

NIA-AA Symposium  
July 19-20, 2018 – Chicago, IL

Matthias Arnold

# Metabolomics: Readout of the physiological state of a biological system



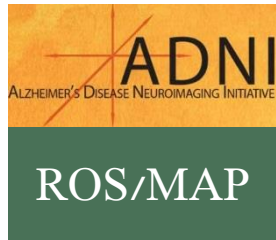
## Metabolism

- captures the combined output of upstream regulatory mechanisms
- tracks external influencers, including diet and environmental exposures
- is the molecular layer most closely linked to a phenotype or disease

# Mission of ADMC: Metabolomics for AMP-AD and M<sup>2</sup>OVE-AD

## METABOLOMICS DATA GENERATION

$N_{\text{metabolites}} \sim 1000$   
in up to 1600 subjects



- Targeted metabolomics
- Targeted bile acid profiles
- Non-targeted broad metabolomics
- Non-targeted broad lipidomics

## DATA PROCESSING AND QC

Raw data

### Primary QC

Remove poor quality samples  
Remove structured missing data

### Univariate QC

Samples: high % missing, non-fasting  
Analytes: high CV, low ICC, high % missing

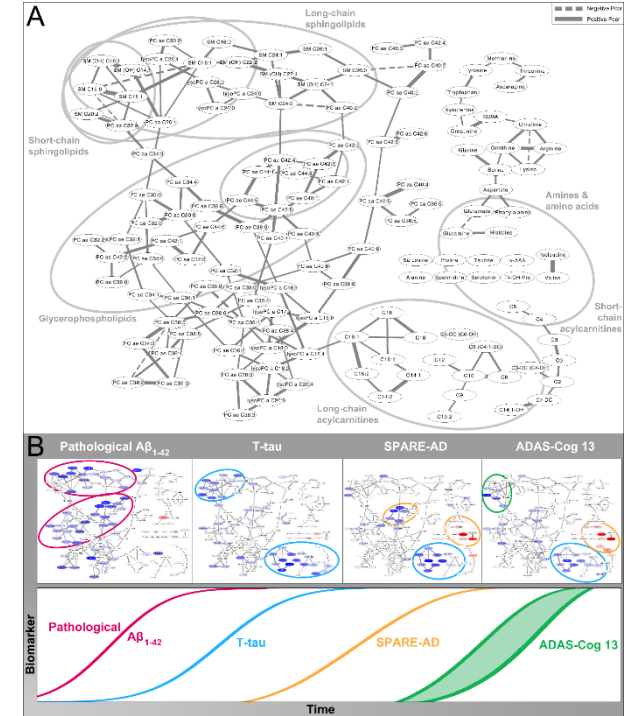
### Data imputation

### Data normalization

### Multivariate outlier removal

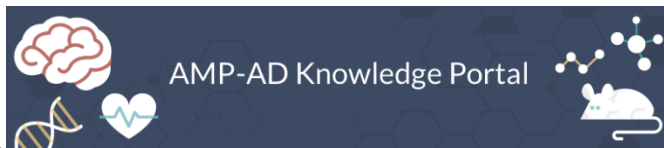
Filtered, high quality data

## DATA ANALYSIS



Toledo et al., Alz Dement, 2017

## OPEN SCIENCE – SHARING DATA / CODE / RESULTS

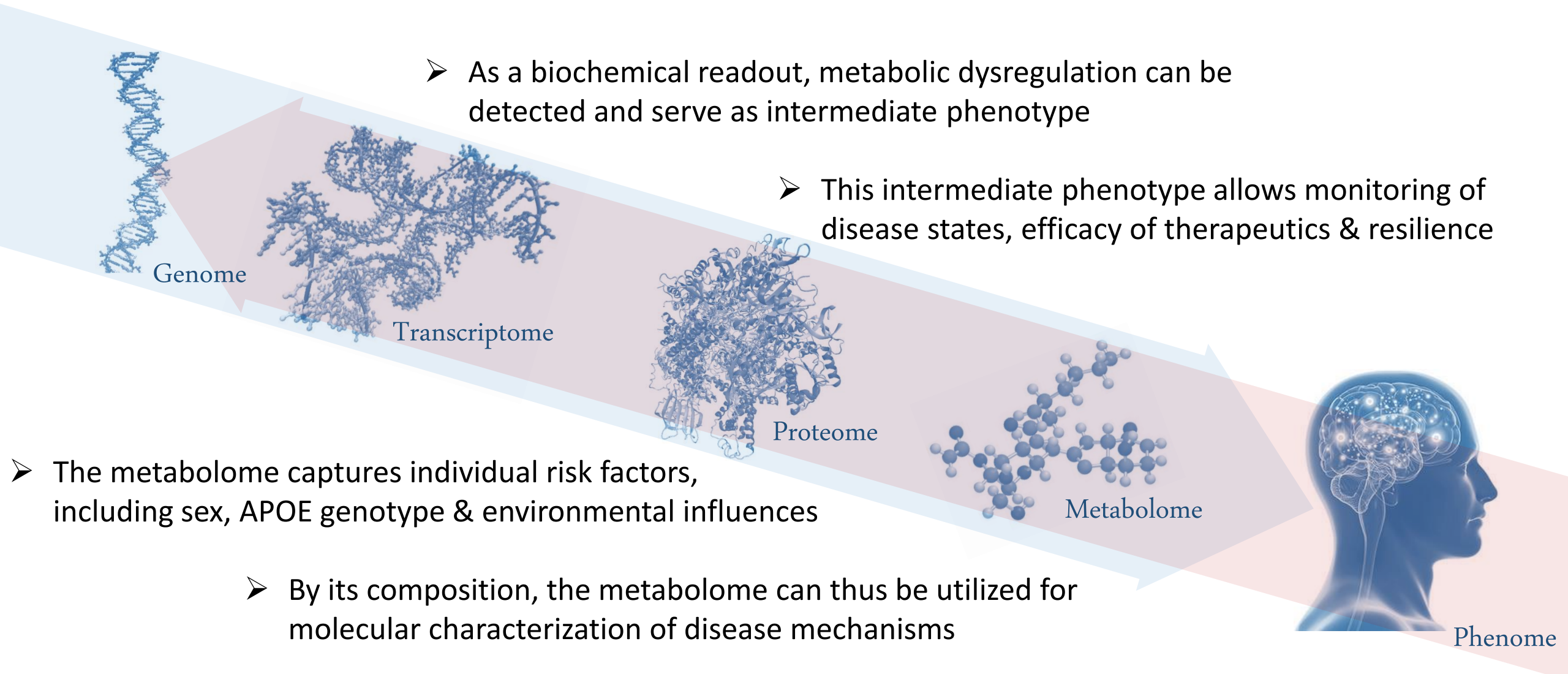


# Integrative Metabolomics: Target Discovery and Prioritization

ACCELERATING MEDICINES PARTNERSHIP (AMP)

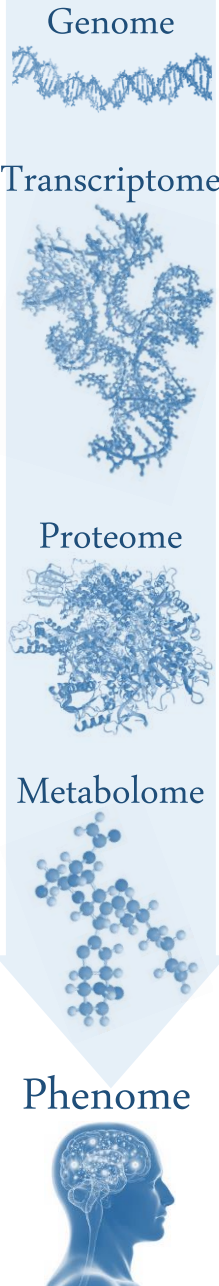
ALZHEIMER'S DISEASE - Target Discovery and Preclinical Validation Project

# Target discovery: Metabolite levels as intermediate phenotype of disease



# Target discovery: Linking metabolite levels to potential target genes

- Genome-wide association studies (GWAS) with metabolomics data
- Canonical, knowledge-based pathway information (e.g. enzymatic reactions) and data-driven metabolic pathway reconstruction approaches
- Multi-omics – link metabolomics data to proteomics and transcriptomics
- Big data integration from different population-based cohort studies



## ARTICLES

nature  
genetics

### An atlas of genetic influences on human blood metabolites

So-Youn Shin<sup>1,21,23</sup>, Eric B Fauman<sup>2,23</sup>, Ann-Kristin Petersen<sup>3,23</sup>, Jan Krumsiek<sup>4,23</sup>, Rita Santos<sup>5</sup>, Jie Huang<sup>1</sup>, Matthias Arnold<sup>6</sup>, Idil Erte<sup>7</sup>, Vincenzo Forgetta<sup>8</sup>, Tsun-Po Yang<sup>1</sup>, Klaudia Walter<sup>1</sup>, Cristina Menni<sup>7</sup>, Lu Chen<sup>1,9</sup>, Louella Vasquez<sup>1</sup>, Ana M Valdes<sup>7,10</sup>, Craig L Hyde<sup>11</sup>, Vicky Wang<sup>2</sup>, Daniel Ziemek<sup>2</sup>, Phoebe Roberts<sup>2,22</sup>, Li Xi<sup>2</sup>, Elin Grundberg<sup>8,12</sup>, The Multiple Tissue Human Expression Resource (MuTHER) Consortium<sup>13</sup>, Melanie Waldenberger<sup>14</sup>, J Brent Richards<sup>7,8,15</sup>, Robert P Mohny<sup>16</sup>, Michael V Milburn<sup>16</sup>, Sally L John<sup>17</sup>, Jeff Trimmer<sup>18,21</sup>, Fabian J Theis<sup>4,19</sup>, John P Overington<sup>5</sup>, Karsten Suhre<sup>6,20,24</sup>, M Julia Brosnan<sup>11,24</sup>, Christian Gieger<sup>3,24</sup>, Gabi Kastenmüller<sup>6,24</sup>, Tim D Spector<sup>7,24</sup> & Nicole Soranzo<sup>1,9,24</sup>



## ARTICLE

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OPEN

### Connecting genetic risk to disease end points through the human blood plasma proteome

Karsten Suhre<sup>1,\*</sup>, Matthias Arnold<sup>2,\*</sup>, Aditya Mukund Bhagwat<sup>3,\*</sup>, Richard J. Cotton<sup>3,\*</sup>, Rudolf Engelke<sup>3,\*</sup>, Johannes Raffler<sup>2,\*</sup>, Hina Sarwath<sup>3,\*</sup>, Gaurav Thareja<sup>1,\*</sup>, Annika Wahl<sup>4,5,\*</sup>, Robert Kirk DeLisle<sup>6</sup>, Larry Gold<sup>6</sup>, Marija Pezer<sup>7</sup>, Gordan Lauc<sup>7</sup>, Mohammed A. El-Din Selim<sup>8</sup>, Dennis O. Mook-Kanamori<sup>9</sup>, Eman K. Al-Dous<sup>10</sup>, Yasmin A. Mohamoud<sup>10</sup>, Joel Malek<sup>10</sup>, Konstantin Strauch<sup>11,12</sup>, Harald Grallert<sup>4,5,13</sup>, Annette Peters<sup>5,13,14</sup>, Gabi Kastenmüller<sup>2,13</sup>, Christian Gieger<sup>4,5,13,\*</sup> & Johannes Graumann<sup>3,\*</sup>†

# Target discovery & prioritization: Integrated molecular atlas of AD

## Population-based data

- 20 million eQTL associations
- 20,000 pQTL associations
- 500,000 mQTL associations



Databases and ontologies

**SNiPA: an interactive, genetic variant-centered annotation browser**

Matthias Arnold<sup>1,†</sup>, Johannes Raffler<sup>1,†</sup>, Arne Pfeufer<sup>1</sup>, Karsten Suhre<sup>1,2</sup> and Gabi Kastenmüller<sup>1,\*</sup>

*Bioinformatics*, 31(8), 2015, 1334–1336  
doi: 10.1093/bioinformatics/btu779  
Advance Access Publication Date: 26 November 2014  
Applications Note



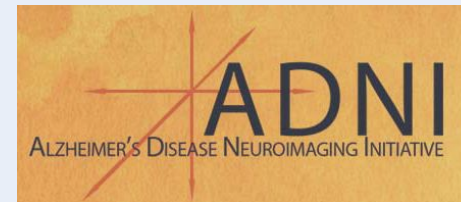
## Genetics of AD & associated markers

- IGAP / UKB 2018 – AD case/control
- IGAP 2017 – Age of onset
- Deming 2016/2017: CSF A $\beta$ , t-/p-tau, CLU
- Beecham 2014: Neuropathological features



## ADNI / ADMC data (about 1500 ADNI samples)

- Comprehensive coverage of markers for AD
- 157 metabolic traits and their associations to AD
- Genetic associations with metabolites & AD
- Metabolite/metabolite links (GGM)

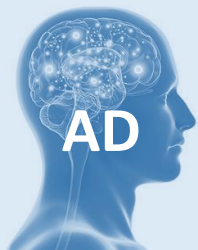


Kwangsik Nho (IU)

# AD & Clinical / diagnostic markers

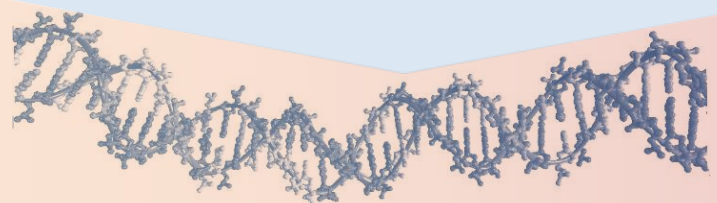
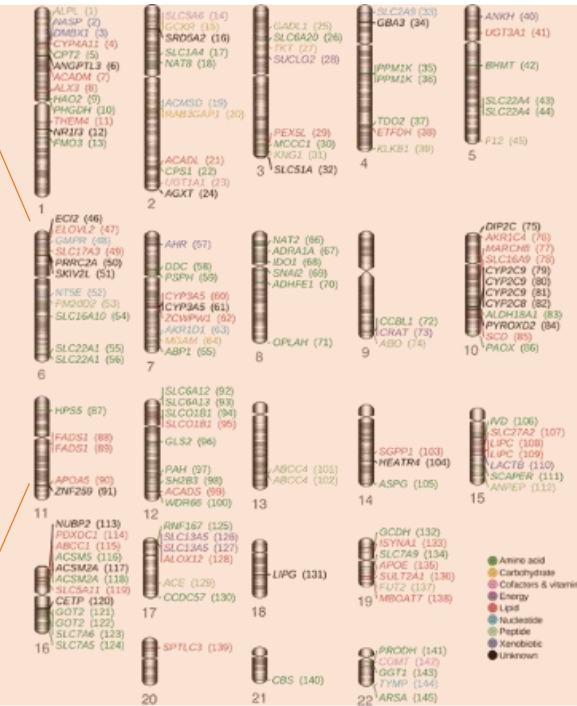
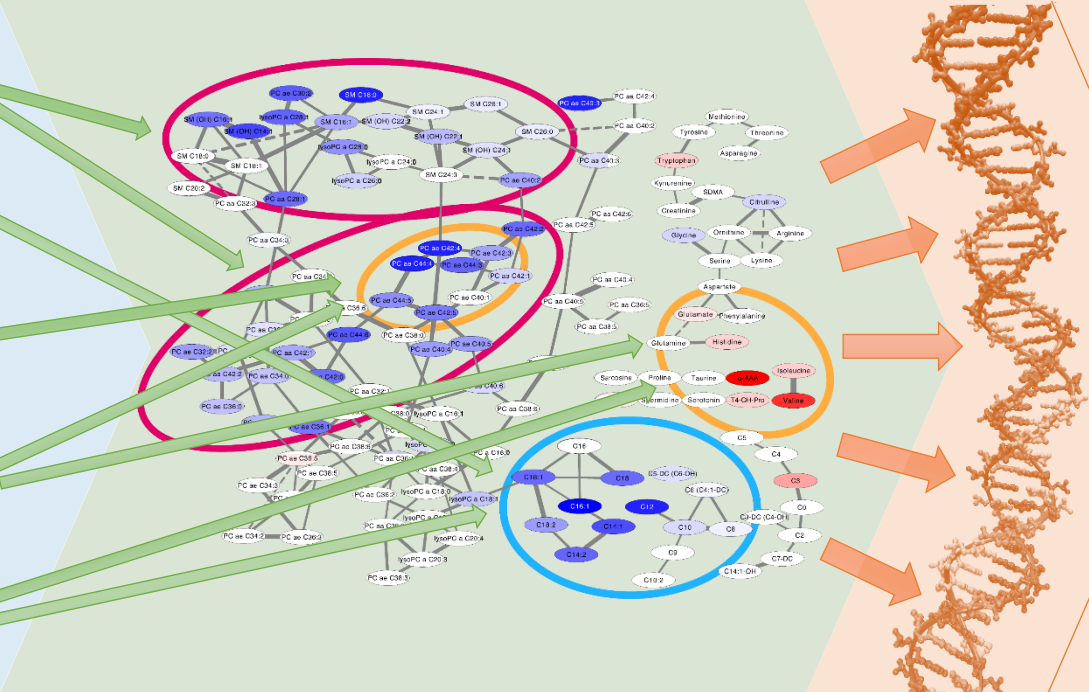
# Intermediate metabolic phenotype

# Metabolite quantitative trait loci



AD

- CSF Aβ
- CSF t-/p-tau
- Functional PET
- MRI / atrophy
- Cognition

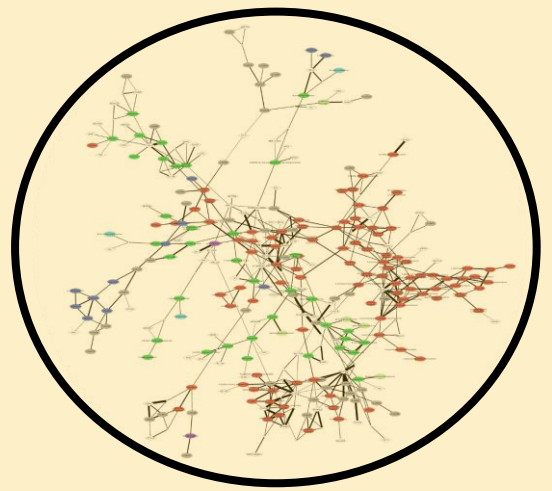


## AD GWAS & Clinical marker QTLs



### Locus annotation

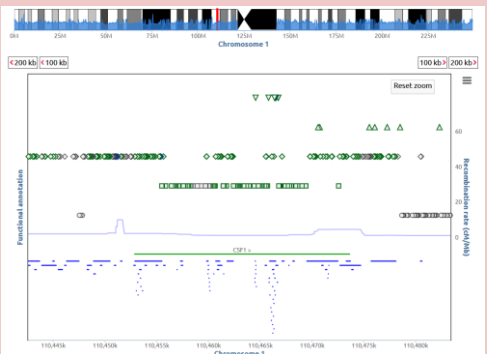
- gene body
- regulatory
- eQTL
- pQTL



## Integrated molecular atlas

### Locus annotation

- gene body
- regulatory
- eQTL
- pQTL







# Integrated molecular atlas of AD: Metabotypes – genetics mirroring AD associations

## MS4A2

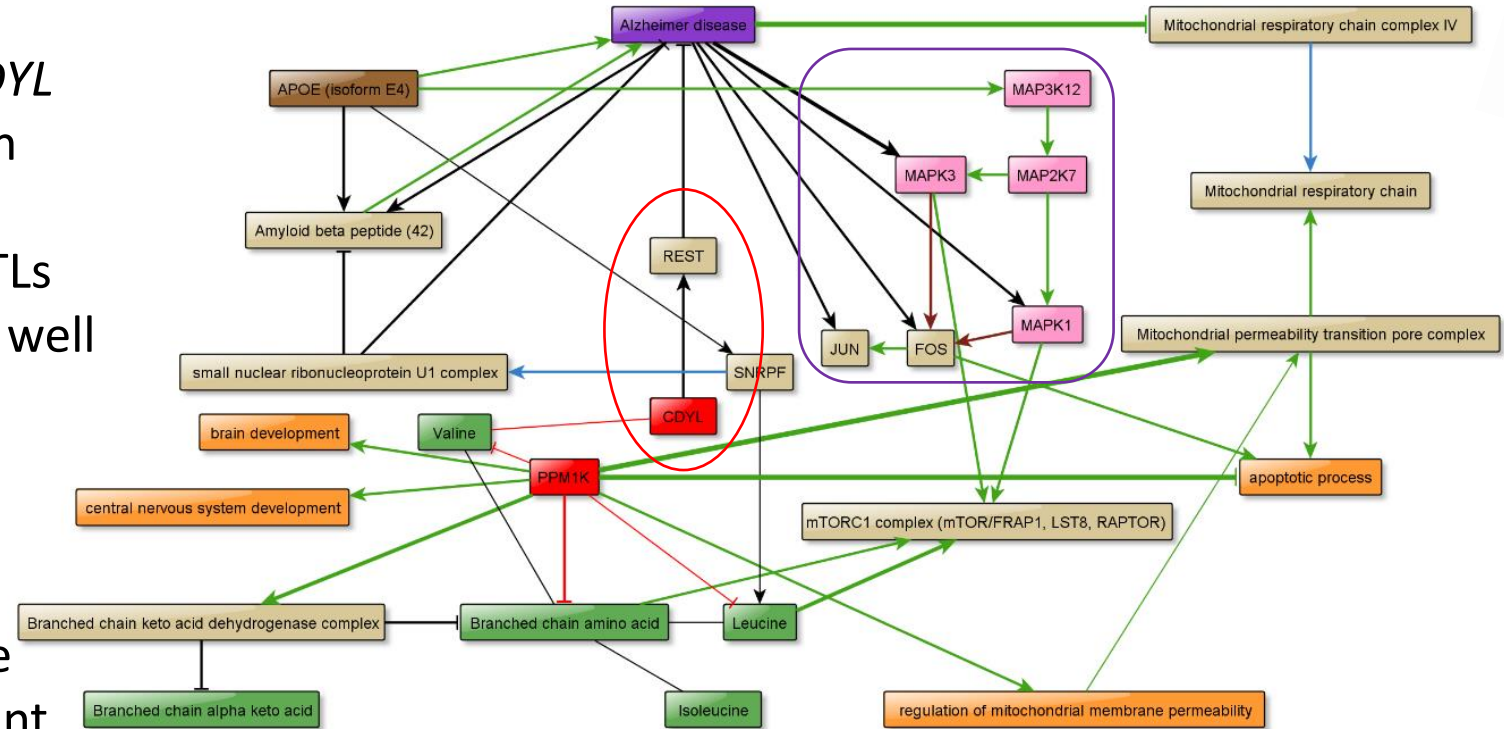
SNP	CHROMOSOME	POSITION	EA_UKB	UKB_AD	EA_ADNI	ADAS-Cog-13	Entorhinal Cortex	Hippocampus	SM C26:0	SM (OH) C24:1	Histidine	Isoleucine	Valine
rs580064	11	59869119	C	-7.7211012	C	-1.7929	1.84375	1.73447	1.31025	1.82391	1.88207	2.23055	2.68027
rs580817	11	59869090	G	-9.392171	G	-1.72216	1.42366	1.39892	1.53536	1.94962	2.58104	2.30839	2.83327
rs487997	11	59871604	C	-9.5962717	C	-1.72216	1.42366	1.39892	1.53536	1.94962	2.58104	2.30839	2.83327
rs574704	11	59867913	G	-9.416886	G	-1.71153	1.41657	1.39502	1.51513	1.93892	2.54668	2.3934	2.9307
rs521952	11	59870196	C	-9.5387986	C	-1.71153	1.41657	1.39502	1.51513	1.93892	2.54668	2.3934	2.9307
rs516478	11	59870788	A	-9.5150729	A	-1.71153	1.41657	1.39502	1.51513	1.93892	2.54668	2.3934	2.9307
rs1786137	11	59873448	C	-9.5177706	C	-1.71153	1.41657	1.39502	1.51513	1.93892	2.54668	2.3934	2.9307
rs558788	11	59852078	G	-10.146167	G	NA	NA	1.33734	NA	1.45445	NA	1.5447	1.31921
rs1813217	11	59872498	C	-10.606488	C	-1.65956	1.31372	1.53462	1.35704	1.70071	2.72769	2.08066	2.034
rs11230147	11	59877394	T	-10.766301	T	-1.61672	NA	1.51784	1.35704	1.70071	2.72769	2.08066	2.034
rs4939311	11	59877967	T	-10.675478	T	-1.61672	NA	1.51784	1.35704	1.70071	2.72769	2.08066	2.034
rs1125357	11	59885493	C	-10.541011	C	-1.5516	NA	1.34056	1.3919	1.7602	2.80162	2.06722	2.06419
rs2855017	11	59866309	T	-10.540437	T	-1.57757	NA	1.51004	1.37428	1.68888	2.76675	2.1303	2.06982
rs17528859	11	59867379	C	-10.661921	C	-1.57757	NA	1.51004	1.37428	1.68888	2.76675	2.1303	2.06982
rs2583471	11	59861814	A	-10.374859	A	-1.54016	NA	1.55549	1.39469	1.81079	2.78516	2.19484	2.10095
rs2070970	11	59861983	T	-10.419124	T	-1.54016	NA	1.55549	1.39469	1.81079	2.78516	2.19484	2.10095
rs2847664	11	59858497	A	-10.063463	A	-1.5071	NA	1.50906	1.39094	1.803	2.78357	2.19314	2.1053
rs2847668	11	59862261	T	-10.398245	T	-1.54485	NA	1.56655	1.42516	1.81987	2.83803	2.22446	2.10763
rs2847663	11	59858036	G	-10.065236	G	-1.47886	NA	1.47965	1.39469	1.82857	2.77211	2.24154	2.12633
rs2583476	11	59857581	A	-9.8880136	A	-1.4537	NA	1.57594	1.45149	1.87095	2.68256	2.24397	2.12668
rs2847666	11	59859576	G	-9.7916411	G	-1.46674	NA	1.6187	NA	1.68256	3.00432	2.27638	2.15945
rs2847667	11	59859609	T	-9.7900287	T	-1.46674	NA	1.6187	NA	1.68256	3.00432	2.27638	2.15945
rs2847655	11	59865671	C	-10.072354	C	-1.45284	NA	1.60995	NA	1.47057	2.88941	2.31336	2.21042
rs555635	11	59877143	C	-9.4811187	C	-1.67861	1.35813	1.38289	1.53536	1.94962	2.58104	2.30839	2.83327
rs563803	11	59878001	A	-9.6684014	A	-1.67861	1.35813	1.38289	1.53536	1.94962	2.58104	2.30839	2.83327
rs540170	11	59880038	T	-9.6528819	T	-1.67861	1.35813	1.38289	1.53536	1.94962	2.58104	2.30839	2.83327
rs574695	11	59881524	C	-9.436675	C	-1.67861	1.35813	1.38289	1.53536	1.94962	2.58104	2.30839	2.83327
rs1441586	11	59856028	C	-8.5691433	C	-1.44069	NA	NA	1.46483	2.06313	2.40682	2.31731	2.84103
rs502419	11	59866175	A	-9.2976439	A	-1.63884	1.34843	1.37551	1.55284	1.93629	2.61816	2.35952	2.87354
rs581133	11	59882306	G	-9.6012043	G	-1.65777	NA	NA	1.55736	1.99012	2.58104	2.37376	2.92775
rs512495	11	59876036	G	-9.5019367	G	-1.66817	1.35115	1.37914	1.51513	1.93892	2.54668	2.3934	2.9307
rs514266	11	59877697	C	-9.6802426	C	-1.66817	1.35115	1.37914	1.51513	1.93892	2.54668	2.3934	2.9307
rs574798	11	59881561	G	-9.600359	G	-1.66817	1.35115	1.37914	1.51513	1.93892	2.54668	2.3934	2.9307
rs556917	11	59858712	T	-8.9302511	T	-1.57284	1.39686	1.39115	1.57971	2.09464	2.62746	2.47978	2.93704
rs502581	11	59860178	T	-9.3011995	T	-1.57284	1.39686	1.39115	1.57971	2.09464	2.62746	2.47978	2.93704
rs1303615	11	59885120	T	-9.5065769	T	-1.54031	NA	NA	1.62912	2.07381	2.63601	2.43498	3.00749
rs564912	11	59885888	T	-9.5600256	T	-1.54242	1.31939	NA	1.58603	2.0215	2.60119	2.45494	3.01068
rs1303621	11	59890674	C	-9.5622631	C	-1.54242	1.31939	NA	1.58603	2.0215	2.60119	2.45494	3.01068

	ADAS-Cog-13	Entorhinal Cortex	Hippocampus
SM C26:0	0.200112	<b>0.002221</b>	0.203232
SM (OH) C24:1	0.095847	<b>8.76E-05</b>	0.074616
Histidine	0.14245	0.106239	<b>0.010791</b>
Isoleucine	<b>0.004752</b>	<b>0.008568</b>	0.05895
Valine	<b>0.003687</b>	<b>0.0197</b>	<b>0.004324</b>

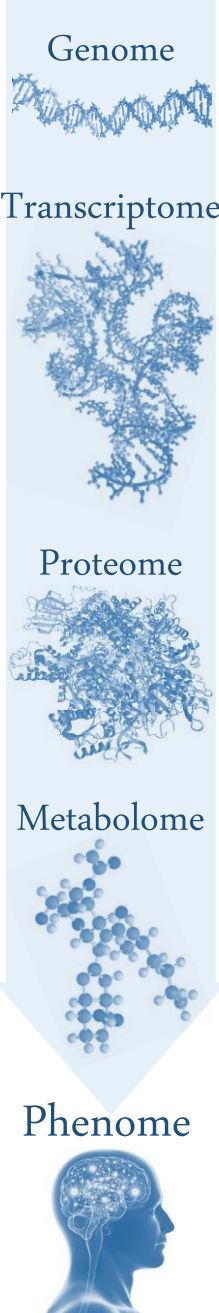
- Genetically influenced metabotype shows the same effect directions as metabotype-trait associations
- Metabolite associations are more significant (> 1 order of magnitude)

# Target discovery & prioritization: Unbiased metabolomics leads to discovery of CDYL

- We observed valine levels to be decreased in AD / associated with cognition
- GWAS for valine yielded the *CDYL* locus as top-ranking association
- Our data lists hippocampal eQTLs for *CDYL* for the same locus, as well as additional QTLs
- *CDYL* is a co-factor of REST
- *REST* and binding partners have been reported to have significant neuroprotective effects (e.g. *Lu et al., Nature, 2014*)

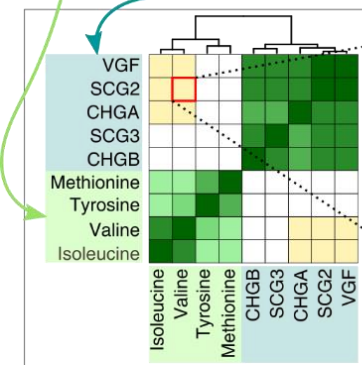
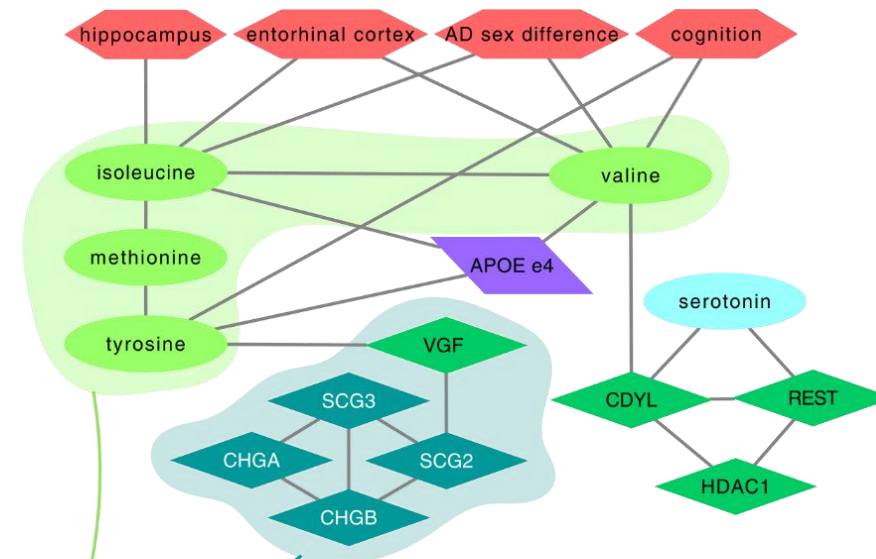


*CIDeR – curated disease networks  
Lechner et al., Genome Biol, 2012*



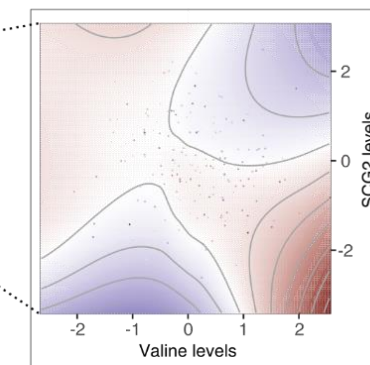
# Target discovery & prioritization: Multi-omics to strengthen confidence in targets

- CDYL regulates enzymes in pathways for valine degradation
- Closely linked amino acids are associated with genetic variants in *VGF*
- *VGF* interacts / is co-regulated with granins, neuroendocrine secretory granule proteins
- Interaction analysis of AA levels and CSF granin/*VGF* levels revealed significant interaction effects on cognition
- Literature shows that REST regulates some granins → disturbed REST binding specificity



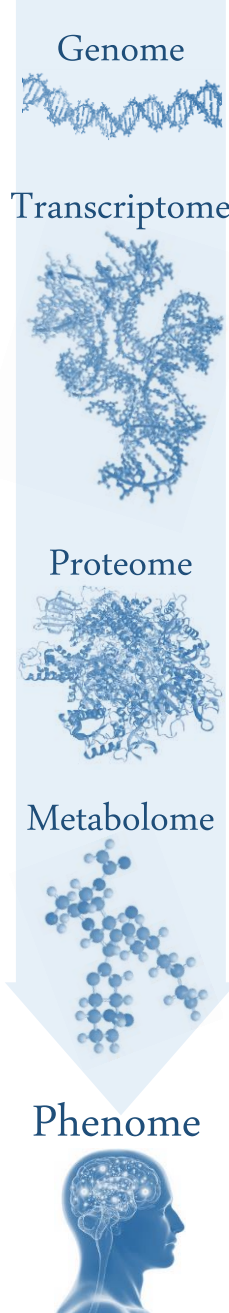
Correlation heatmap

-1  $\rho$  1



Interaction contour/level plot

worse *Cognition* better

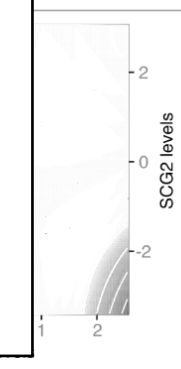
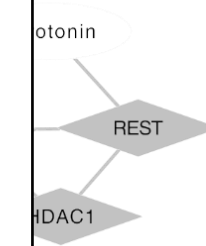
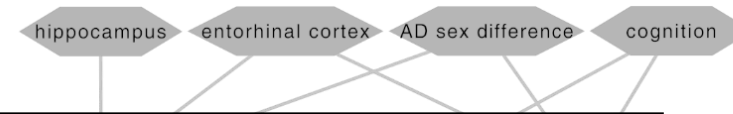


# Target discovery & prioritization: Integrated hypotheses for sets of targets

- CDYL regulates enzymes in pathways for valine degradation
- Closely linked with genetic variants
- VGF interacts with neuroendocrine system
- Interaction among granin/VGF levels and interaction effects
- Literature shows that granins → disturbed REST binding specificity

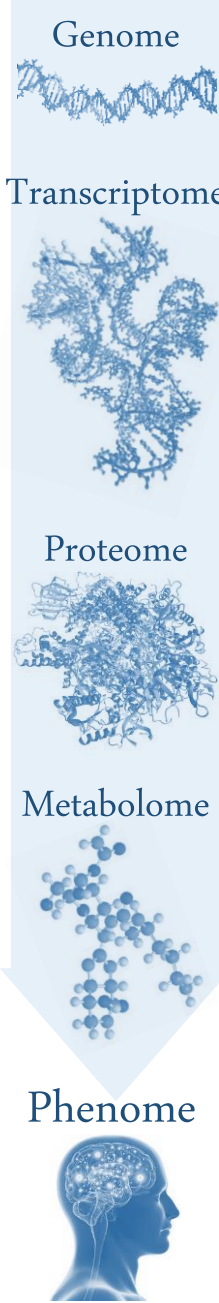
## ***CDYL – REST – HDAC1 – VGF + ACE?***

- The CDYL locus is associated with blood pressure
- It is also associated with dipeptides
- We hypothesized that there may be a link to ACE that
  - regulates blood pressure and
  - functions as dipeptidase
- ACE detected as genetic risk gene in the new IGAP study

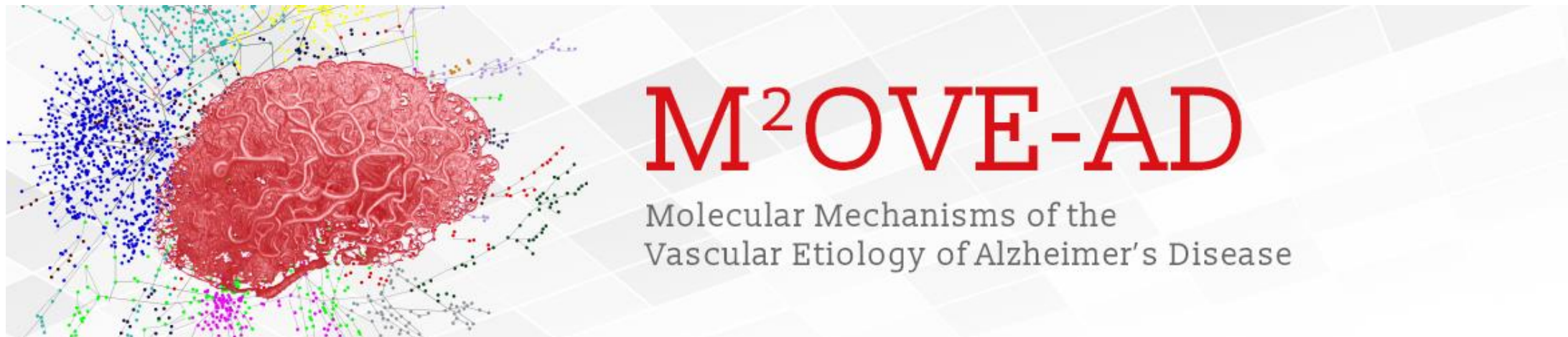


Correlation heatmap  
-1  $\rho$  1

Interaction contour/level plot  
worse *Cognition* better



# Integrative Metabolomics: Disease Sub-Classification for Precision Medicine



# Sex-differences in the blood metabolome


## KORA F4 (German population-based cohort)

- Non-targeted metabolomics platform (Metabolon):  
n ~ 1800; 507 metabolites (different pw)  
Krumsiek et al., Metabolomics 2015  
  
=> **180 of 507 metabolites** show significant differences
- Targeted metabolomics platform (Biocrates p150):  
n ~ 3000; 131 metabolites (mostly lipids & amino acids)  
Mittelstrass et al., PloS Genetics, 2011  
  
=> **102 of 131 metabolites** show significant differences

Metabolomics (2015) 11:1815–1833  
DOI 10.1007/s11306-015-0829-0

ORIGINAL ARTICLE

## Gender-specific pathway differences in the human serum metabolome

Jan Krumsiek<sup>1,2</sup>  · Kirstin Mittelstrass<sup>3,4</sup> · Kieu Trinh Do<sup>1</sup> · Ferdinand Stückler<sup>1</sup> · Janina Ried<sup>5</sup> · Jerzy Adamski<sup>2,6,7</sup> · Annette Peters<sup>2,4,8</sup> · Thomas Illig<sup>9</sup> · Florian Kronenberg<sup>10</sup> · Nele Friedrich<sup>11,12</sup> · Matthias Nauck<sup>11,12</sup> · Maik Pietzner<sup>11,12</sup> · Dennis O. Mook-Kanamori<sup>13,14,15</sup> · Karsten Suhre<sup>15,16</sup> · Christian Gieger<sup>3,4</sup> · Harald Grallert<sup>3,4</sup> · Fabian J. Theis<sup>1,17</sup> · Gabi Kastenmüller<sup>2,16</sup>

OPEN  ACCESS Freely available online

PLoS GENETICS

## Discovery of Sexual Dimorphisms in Metabolic and Genetic Biomarkers

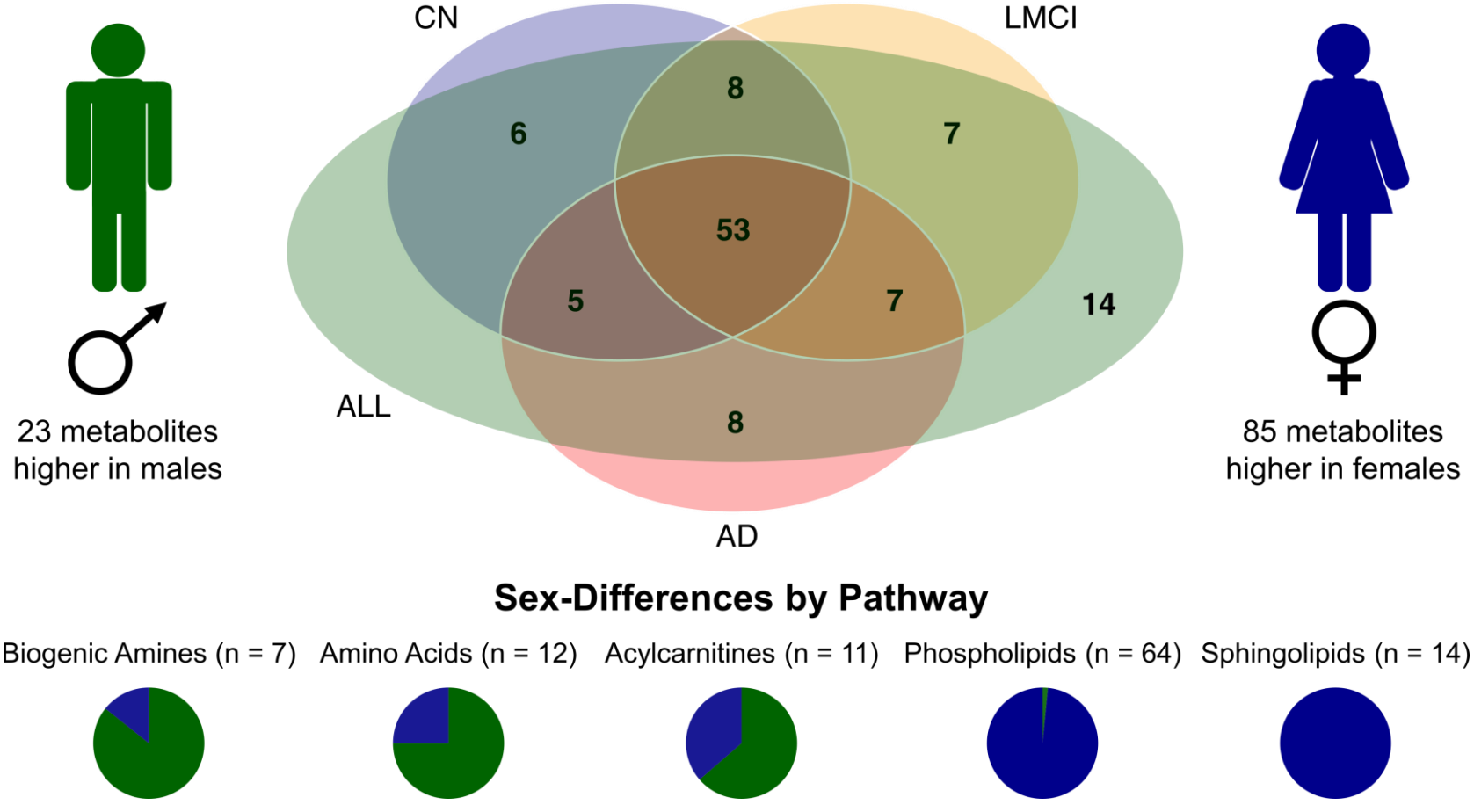
Kirstin Mittelstrass<sup>1,9</sup>, Janina S. Ried<sup>2,9</sup>, Zhonghao Yu<sup>1,9</sup>, Jan Krumsiek<sup>3</sup>, Christian Gieger<sup>2</sup>, Cornelia Prehn<sup>4</sup>, Werner Roemisch-Margl<sup>3</sup>, Alexey Polonikov<sup>5</sup>, Annette Peters<sup>6</sup>, Fabian J. Theis<sup>3</sup>, Thomas Meitinger<sup>7,8</sup>, Florian Kronenberg<sup>9</sup>, Stephan Weidinger<sup>10</sup>, Heinz Erich Wichmann<sup>11,12,13</sup>, Karsten Suhre<sup>3,14,15</sup>, Rui Wang-Sattler<sup>1</sup>, Jerzy Adamski<sup>4,16</sup>\*, Thomas Illig<sup>1</sup>\*

... many other studies showed the same trends

# Sex-differences in the blood metabolome in AD

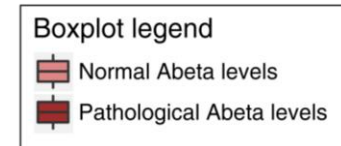
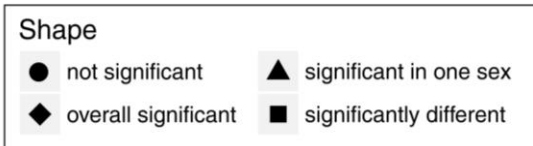
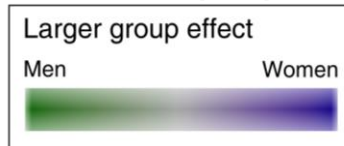
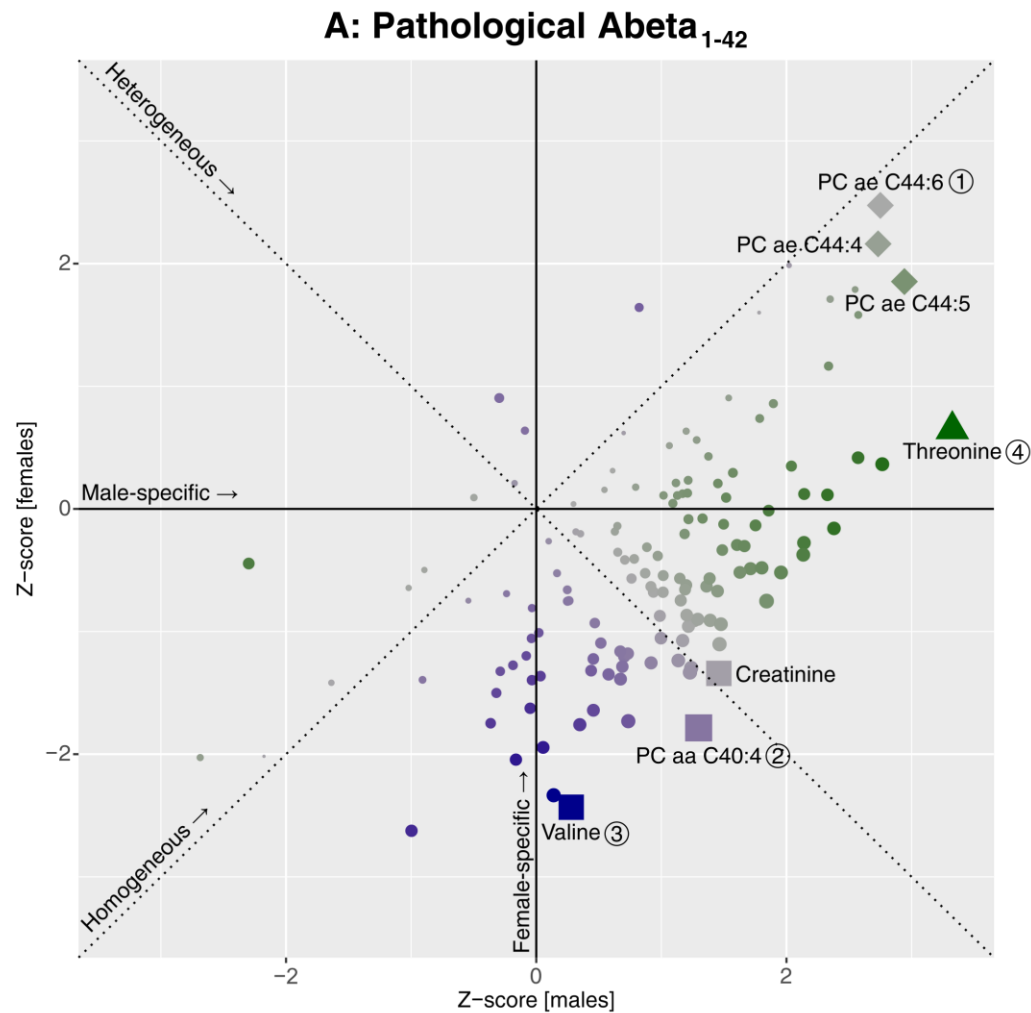
ADNI – 1/GO/2 (n = 1,531)

- In ADNI, we find significant sex-differences for **108 of 140 metabolites**
- Of those, 70 are also significantly different in KORA with **consistent effect directions**
- Metabolic sex-differences **are not changed by AD**

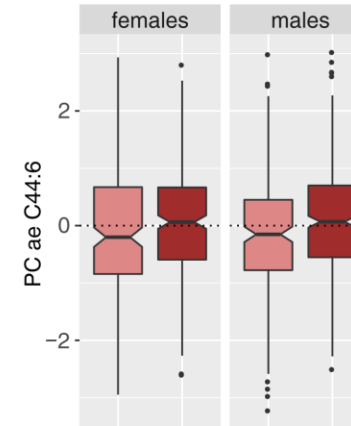




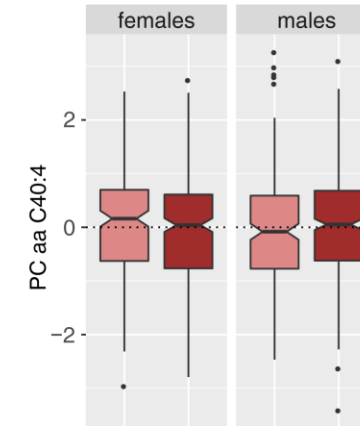
# Sex-differences in metabolic effects on CSF $A\beta_{1-42}$ pathology



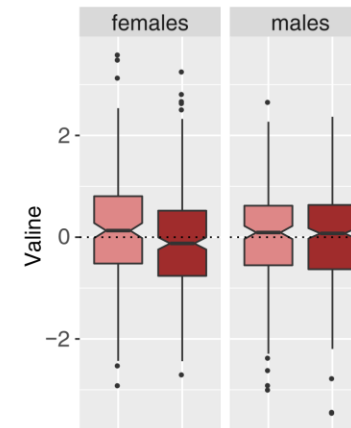
① Homogeneous effect



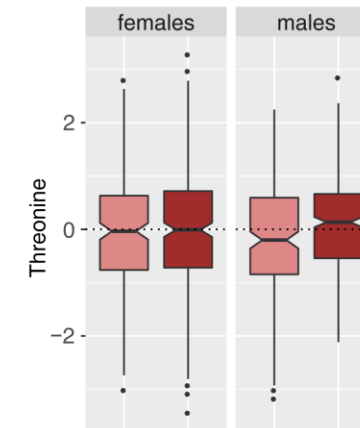
② Heterogeneous effect



③ Female-specific effect



④ Male-specific effect

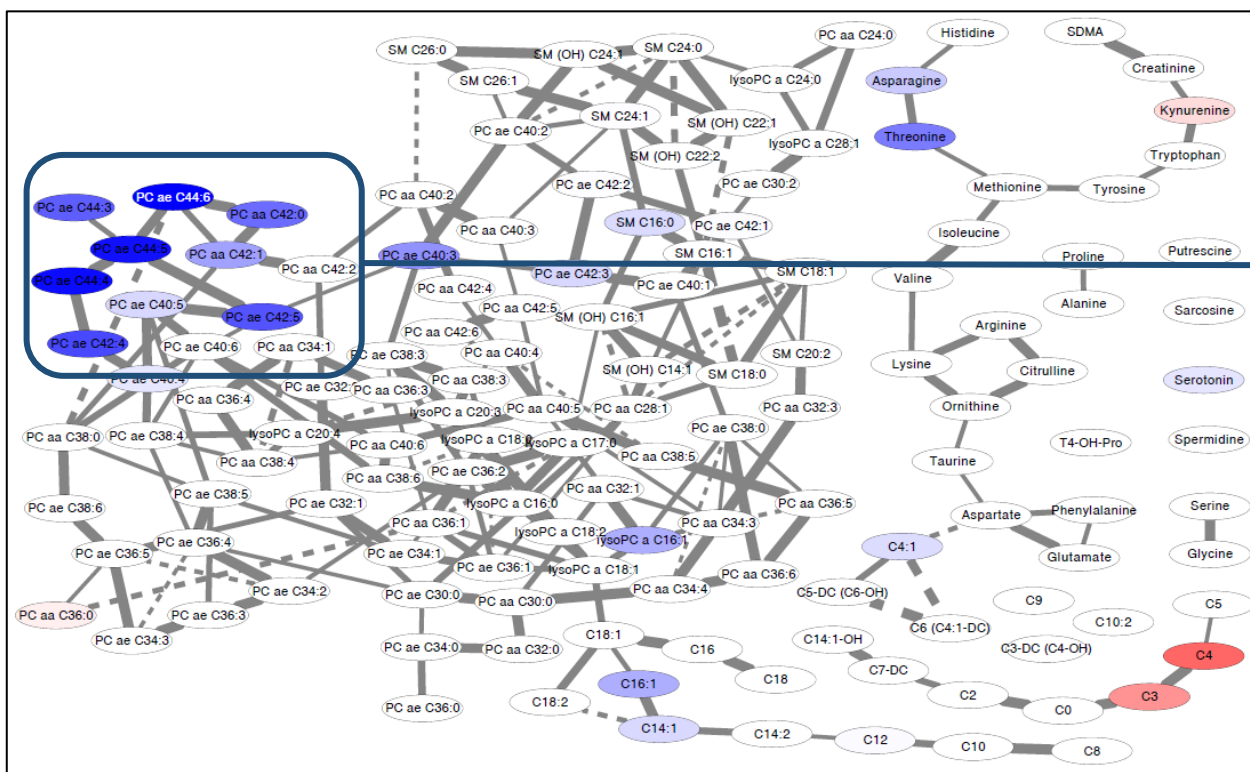


# Disease sub-classification: CSF $A\beta_{1-42}$ pathology

Targeted metabolomics platform (Biocrates AbsoluteIDQ® p180)

ADNI-1/GO/2: 1531 samples

Associations with pathological  $A\beta_{1-42}$  threshold



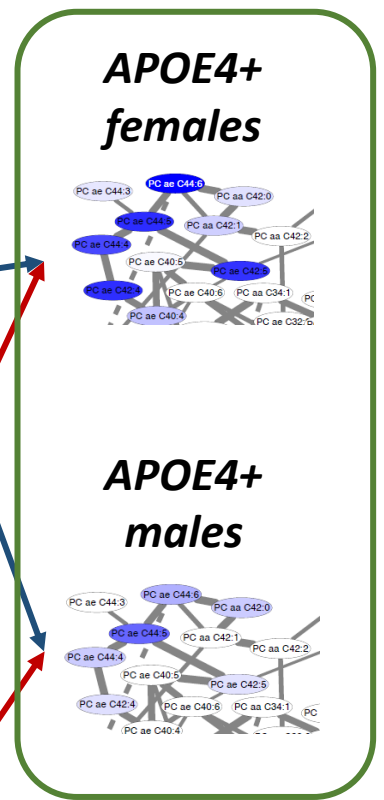
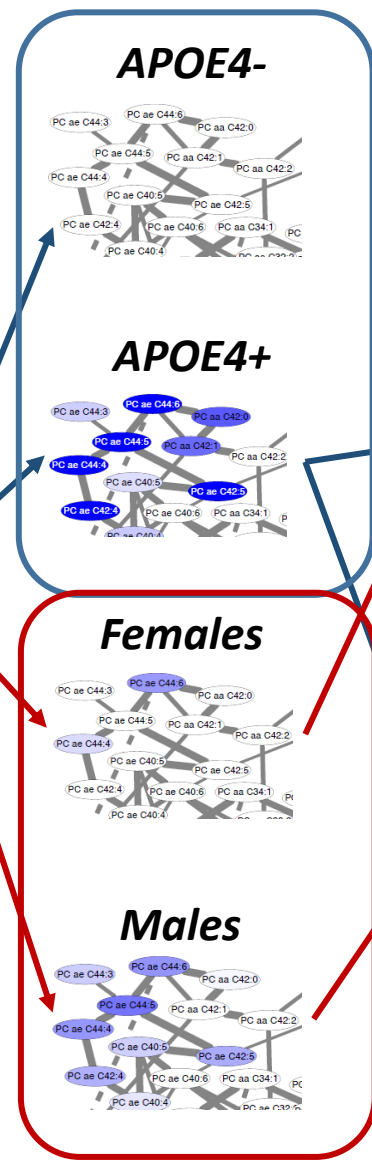
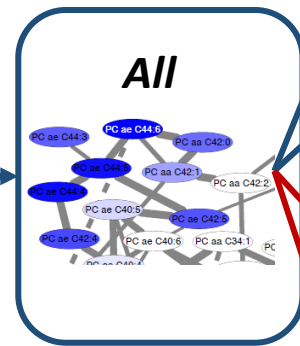
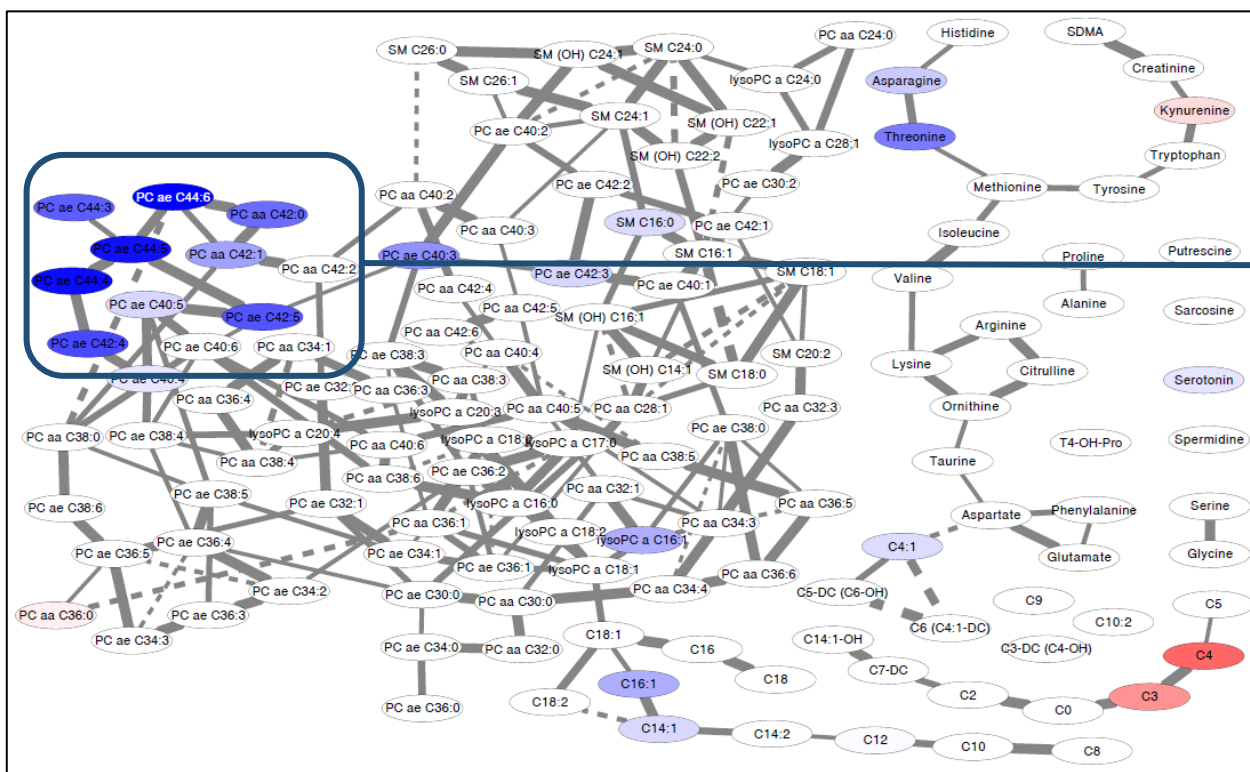
*Tightly connected module of related phosphatidylcholines*

# Disease sub-classification: CSF A $\beta_{1-42}$ pathology

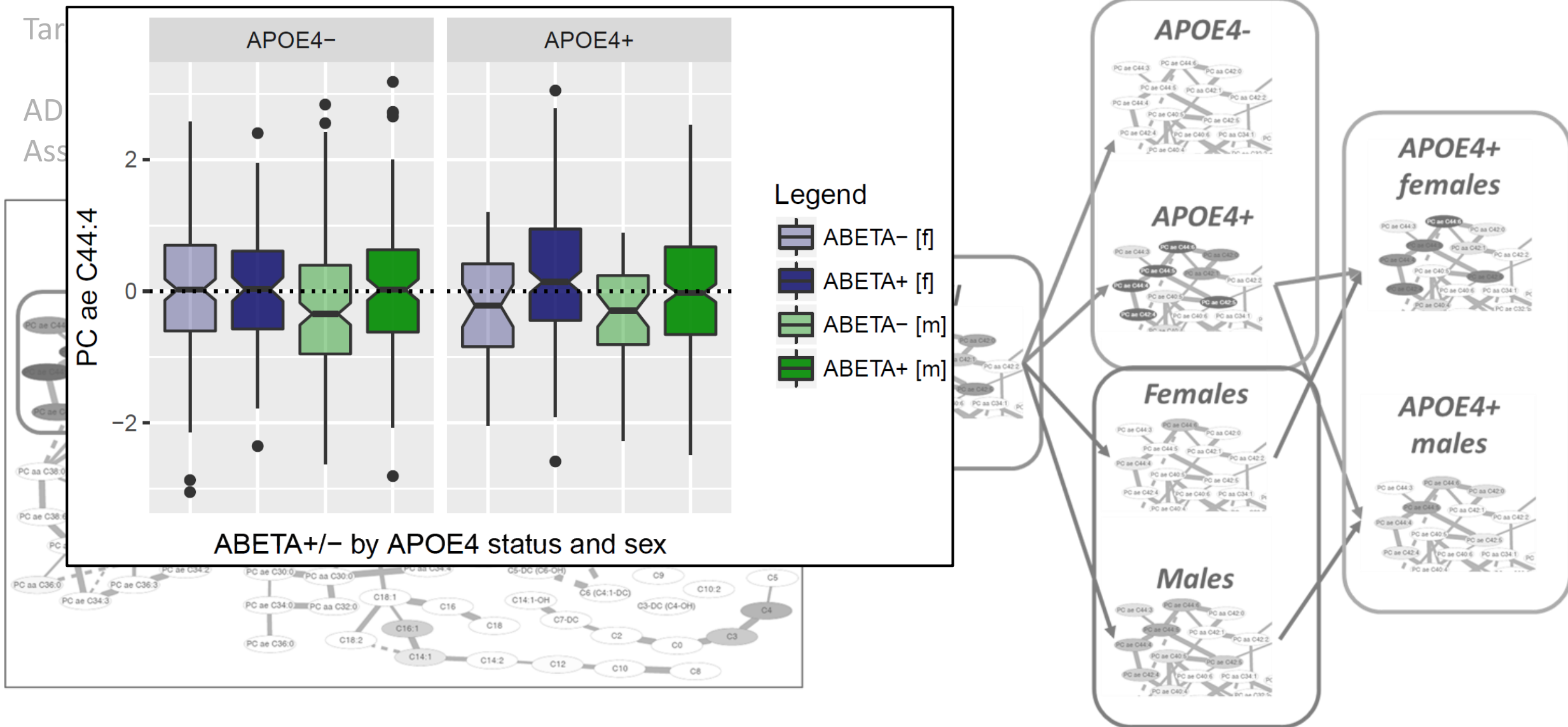
Targeted metabolomics platform (Biocrates AbsoluteIDQ<sup>®</sup> p180)

ADNI-1/GO/2: 1531 samples

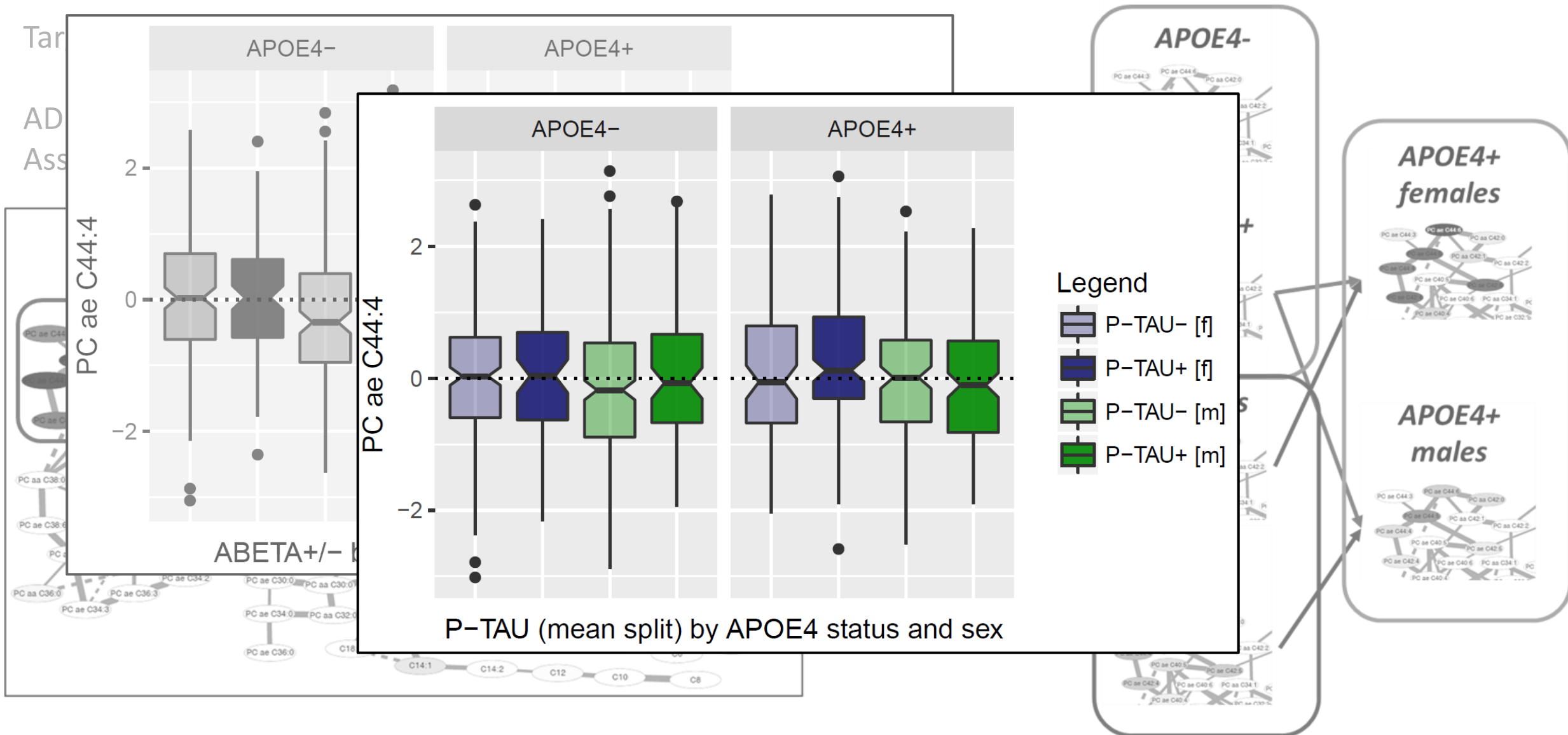
Associations with pathological A $\beta_{1-42}$  threshold



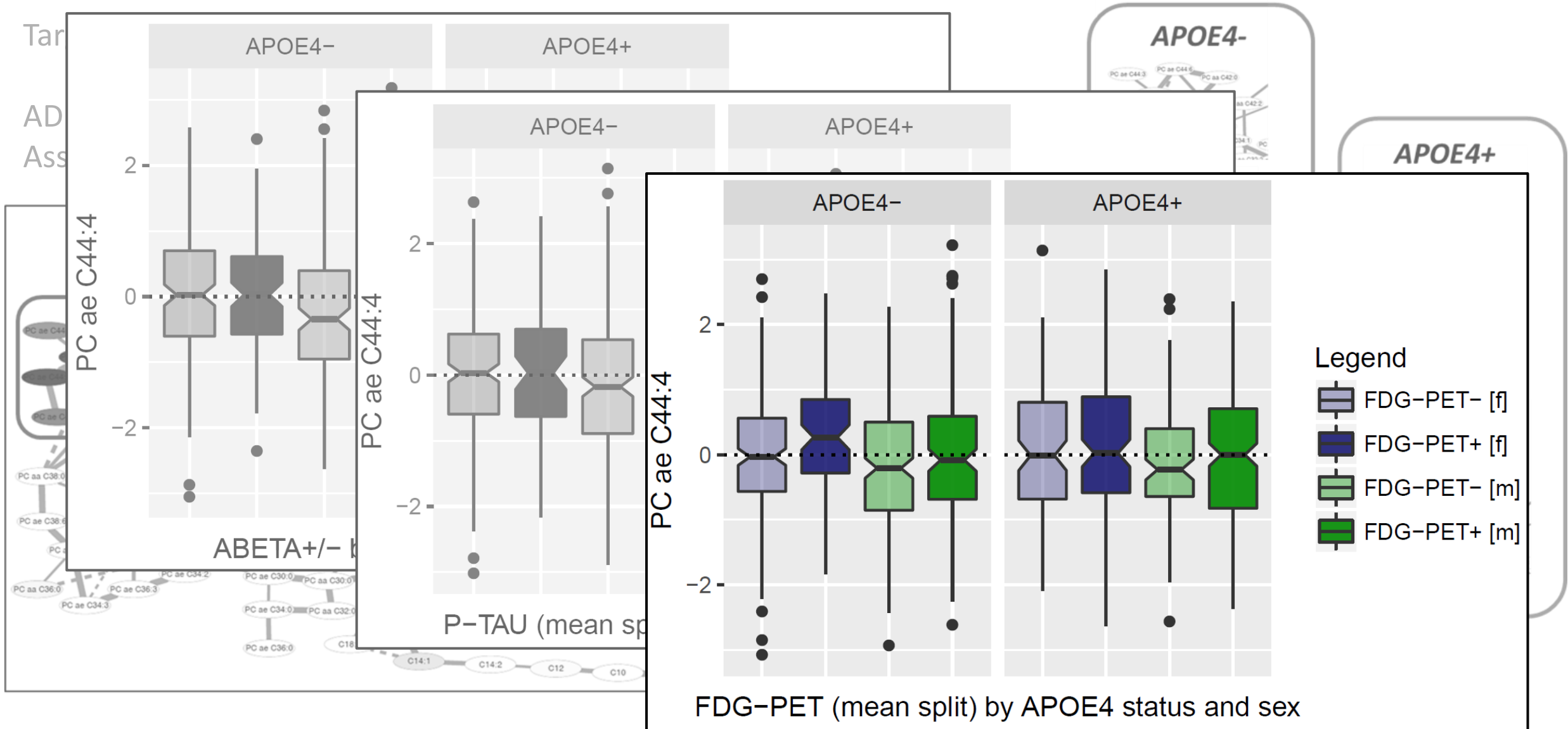
# Disease sub-classification: CSF $A\beta_{1-42}$ pathology



# Disease sub-classification: CSF tau pathology



# Disease sub-classification: Brain glucose hypometabolism

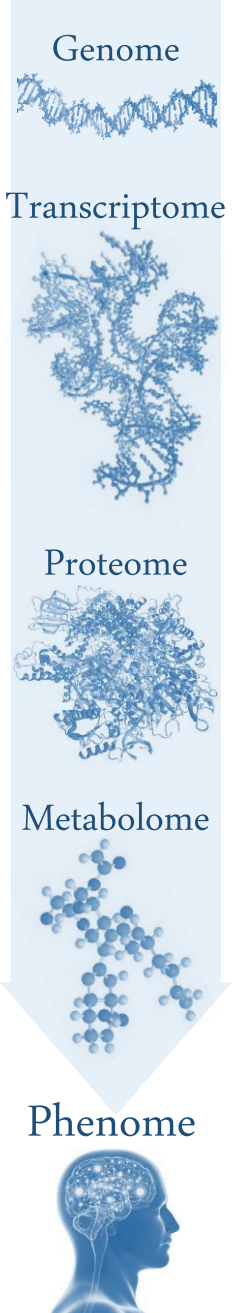


# Integrative Metabolomics: Target Discovery, Prioritization & Sub-Classification

**Metabolomics – a molecular readout for functional hypotheses**

## Ongoing studies and next steps:

- Longitudinal metabolomics profiling across multiple cohorts to capture early changes
- Understand the relationship between the blood and brain metabolome
- Large-scale cross-omics/neuroimaging data integration and use of metabotypes (sets of metabolites) to identify disease subtypes



# Alzheimer's Disease Metabolomics Consortium

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Suzana Petanceska (NIH/NIA)

### ADNI

John Hsiao (NIH/NIA/ERP)  
Michael Weiner and  
leadership of ADNI

- NIA - R01 AG057452** - *Metabolic Network Analysis of Biochemical Trajectories in Alzheimer's Disease*
- NIA - R01 AG046171** - *Metabolic Networks and Pathways in Alzheimer's Disease*
- NIA - R01 AG051550** - *Metabolic Signatures Underlying Vascular Risk Factors for Alzheimer-type Dementias*
- FNIH #DAOU16AMPA** - *An integrated AMP-AD biomarker discovery study*