

Machine Learning for Healthcare

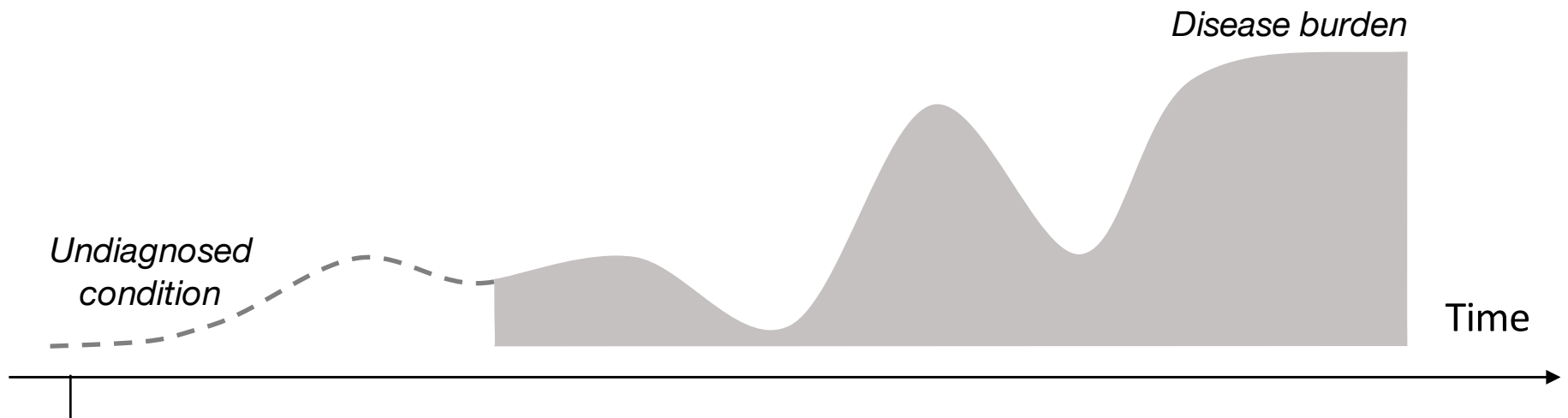
HST.956, 6.S897

Lecture 18: Disease progression modeling & subtyping, Part 1

David Sontag



Prognosis: Where is a patient in their disease trajectory?
When will the disease progress? How will treatment affect
disease progression?



Predicted risk of developing disease or predicting outcome



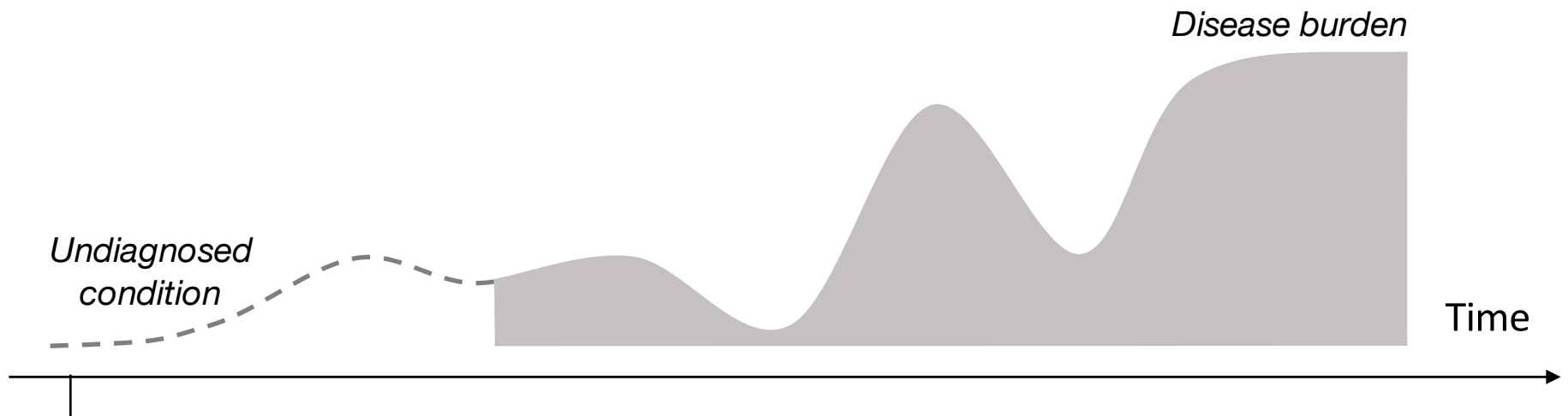
Example: Multiple myeloma

- ▶ Rare blood cancer
- ▶ MMRF CoMMpass Study has ~1000 patients

Myeloma Staging Systems

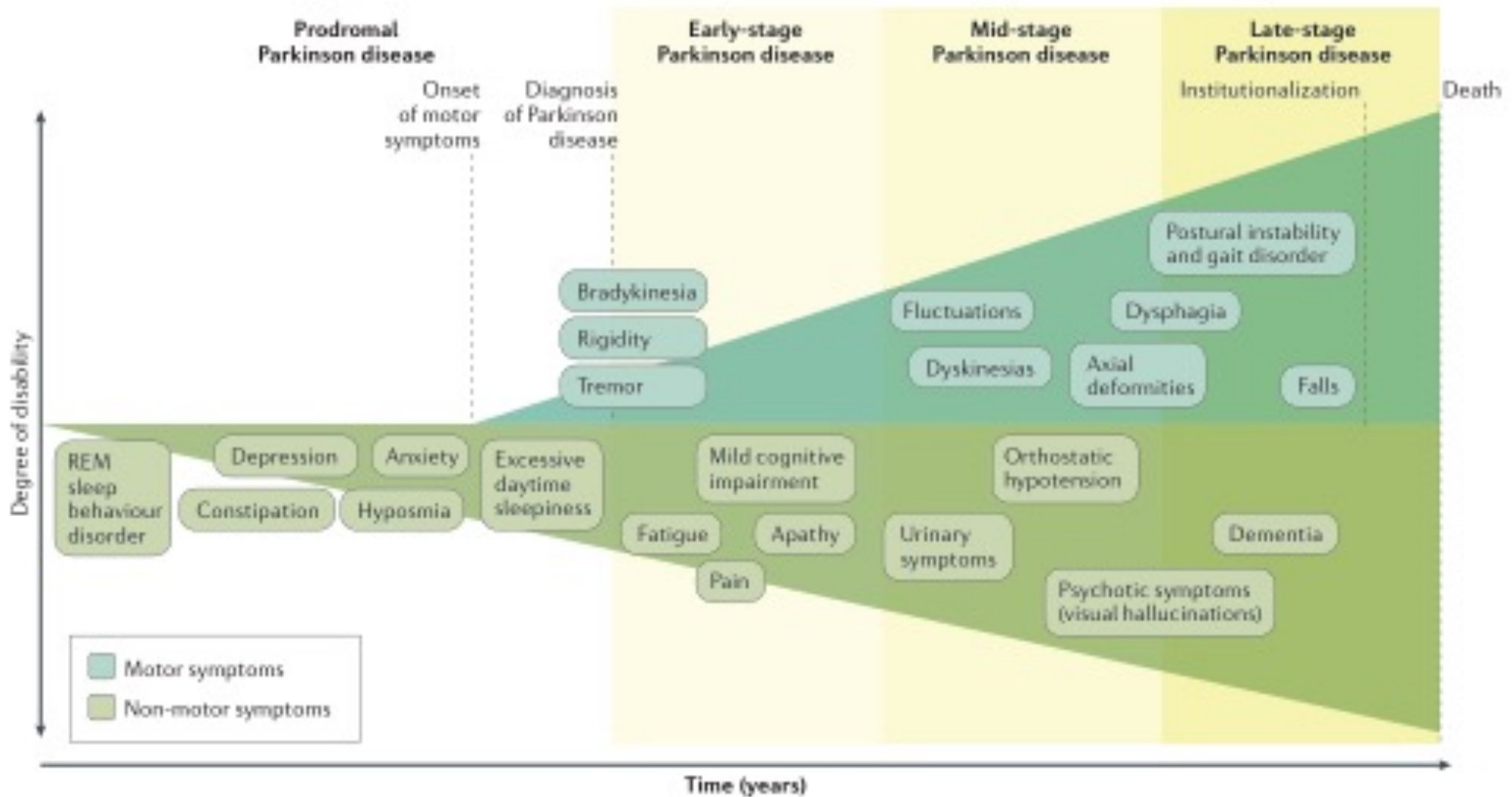
Stage	Durie-Salmon Staging System	Revised International Staging System
I	<p>All of the following:</p> <ul style="list-style-type: none"> ○ Hemoglobin >10.5 g/dL ○ Serum calcium value normal or ≤12 mg/dL ○ X-ray studies of bone, normal bone structure (scale 0) or solitary bone plasmacytoma only ○ Low M-component production rate IgG value <5 g/dL; IgA value <3 g/dL ○ Urine light chains <4g/24 hours 	<ul style="list-style-type: none"> ○ Serum albumin >3.5 g/dL ○ Serum β_2-microglobulin <3.5 mg/L ○ No high-risk cytogenetics ○ Normal serum lactate dehydrogenase level
II	<p>Neither stage I nor stage III</p> <ul style="list-style-type: none"> ○ A—No renal failure (creatinine ≤2 mg/dL) ○ B—Renal failure (creatinine >2 mg/dL) 	<p>Neither stage I nor stage III</p>
III	<ul style="list-style-type: none"> ○ Hemoglobin value <8.5 g/dL ○ Serum calcium value >12 mg/dL ○ X-ray studies of bone, >3 lytic bone lesions ○ High M-component production rate IgG value >7 g/dL; IgA value >5 g/dL ○ Urine light chains >12 g/24 hours 	<ul style="list-style-type: none"> ○ Serum β_2-microglobulin >5.5 mg/L ○ High-risk cytogenetics t(4;14) t(14;16) del(17p) ○ Elevated serum lactate dehydrogenase level

Descriptive: What does a typical trajectory look like?



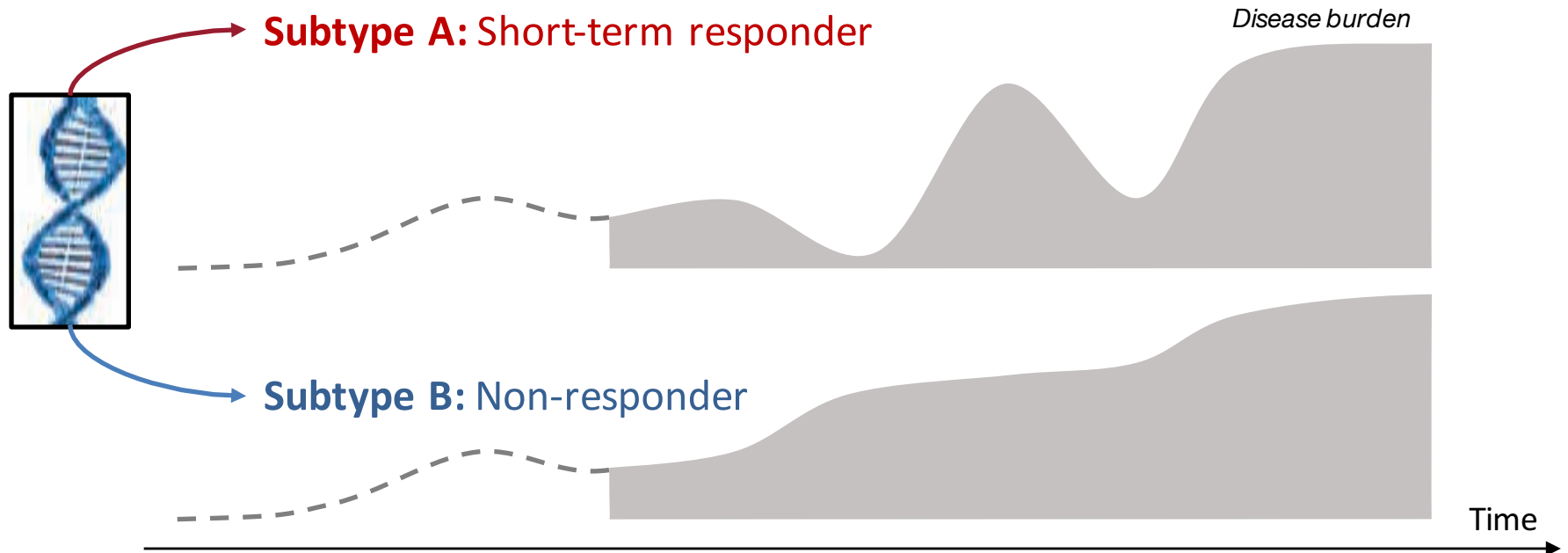
Example: Parkinson's

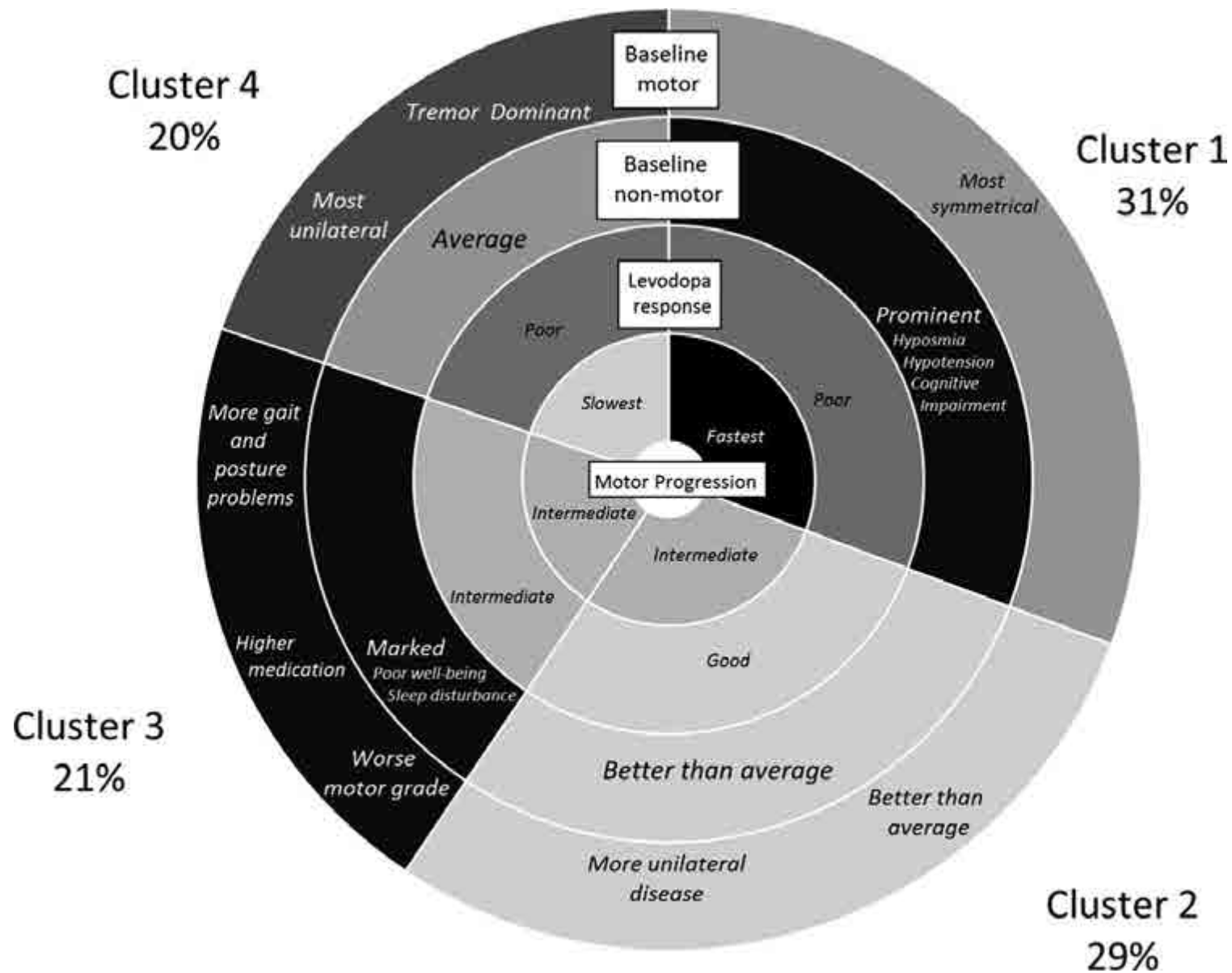
- ▶ Progressive nervous system disorder
- ▶ Affects 1 in 100 people over age 60
- ▶ PPMI dataset follows patients across time



[Poewe et al., Parkinson's disease. *Nature Reviews Disease Primers*, 2017]

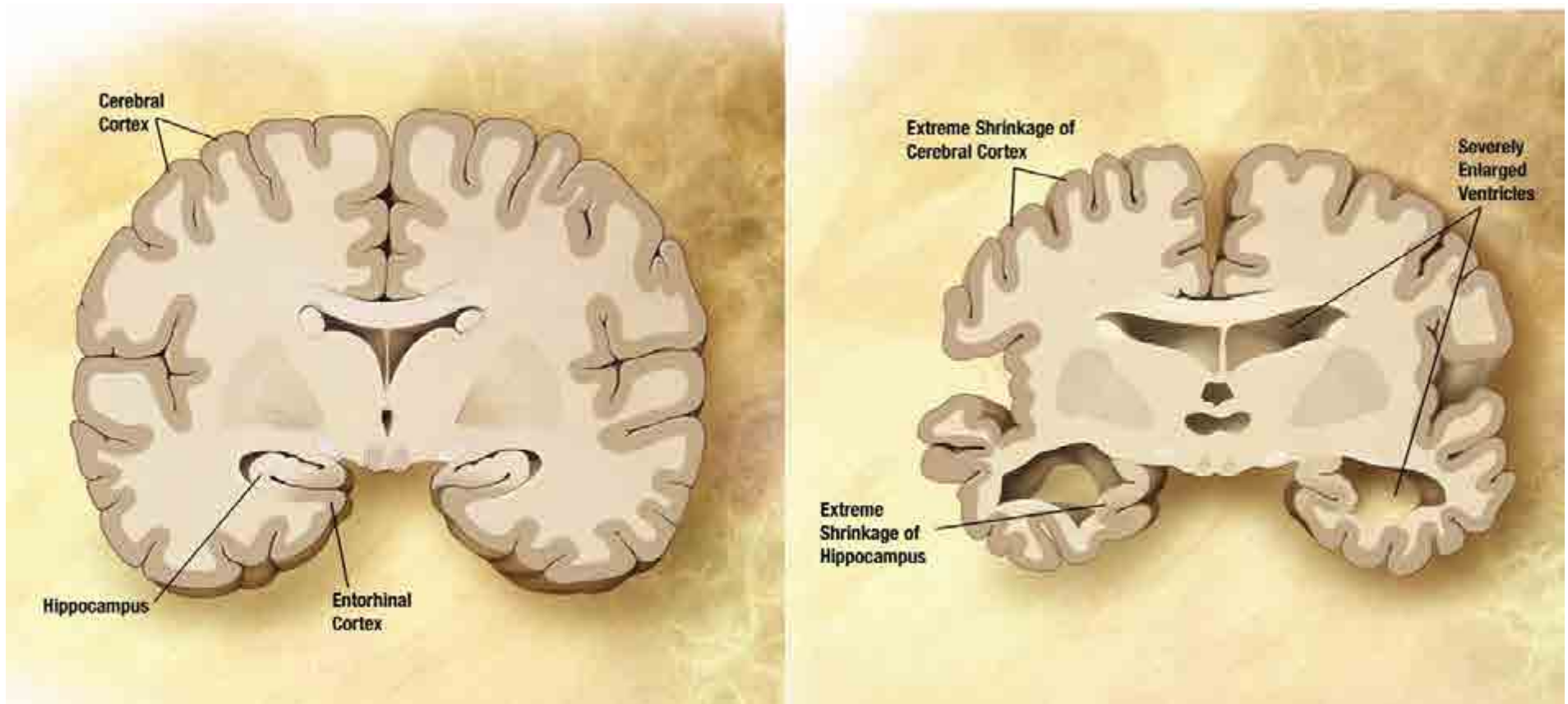
Subtyping: Can we re-define the disease altogether?





[Lawton et al., Developing and validating Parkinson's disease subtypes and their motor and cognitive progression. *J Neurol Neurosurg Psychiatry*, 2018]

Predicting disease progression in Alzheimer's disease



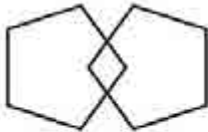
Courtesy of the [NIH](#). Image is in the public domain.

MINI MENTAL STATE EXAMINATION (MMSE)

Name: _____
 DOB: _____
 Hospital Number: _____

Disease status quantified by cognitive score (continuous valued)

One point for each answer. DATE: _____/_____/_____

ORIENTATION Year Season Month Date Time Country Town District Hospital Ward/Floor/5/5/5
REGISTRATION Examiner names three objects (e.g. apple, table, penny) and asks the patient to repeat (1 point for each correct. THEN the patient learns the 3 names repeating until correct)./3/3/3
ATTENTION AND CALCULATION Subtract 7 from 100, then repeat from result. Continue five times: 100, 93, 86, 79, 65. (Alternative: spell "WORLD" backwards: DLROW)./5/5/5
RECALL Ask for the names of the three objects learned earlier./3/3/3
LANGUAGE Name two objects (e.g. pen, watch). Repeat "No ifs, ands, or buts". Give a three-stage command. Score 1 for each stage. (e.g. "Place index finger of right hand on your nose and then on your left ear"). Ask the patient to read and obey a written command on a piece of paper. The written instruction is: "Close your eyes". Ask the patient to write a sentence. Score 1 if it is sensible and has a subject and a verb./2 /1 /3 /1 /1/2 /1 /3 /1 /1/2 /1 /3 /1 /1
COPYING: Ask the patient to copy a pair of intersecting pentagons. /1/1/1
TOTAL:/30/30/30

MMSE scoring
 24-30: no cognitive impairment
 18-23: mild cognitive impairment
 0-17: severe cognitive impairment



© Oxford Medical Education. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/>

Predicting disease progression in Alzheimer's disease

- Goal: Predict disease status in *6, 12, 24, 36, and 48 months*
- Five different regression tasks?
- Challenge: data sparsity
 - Total number of patients is small
 - Labels are noisy
 - Due to censoring, fewer patients at later time points

[Zhou et al., KDD '12]

Predicting disease progression in Alzheimer's disease

- Goal: Predict disease status in 6, 12, 24, 36, and 48 months
- Five different regression tasks?
- Challenge: data sparsity

Number of patients M months after baseline
(Alzheimer's Disease Neuroimaging Initiative)

M06	M12	M24	M36	M48
648	642	569	389	87

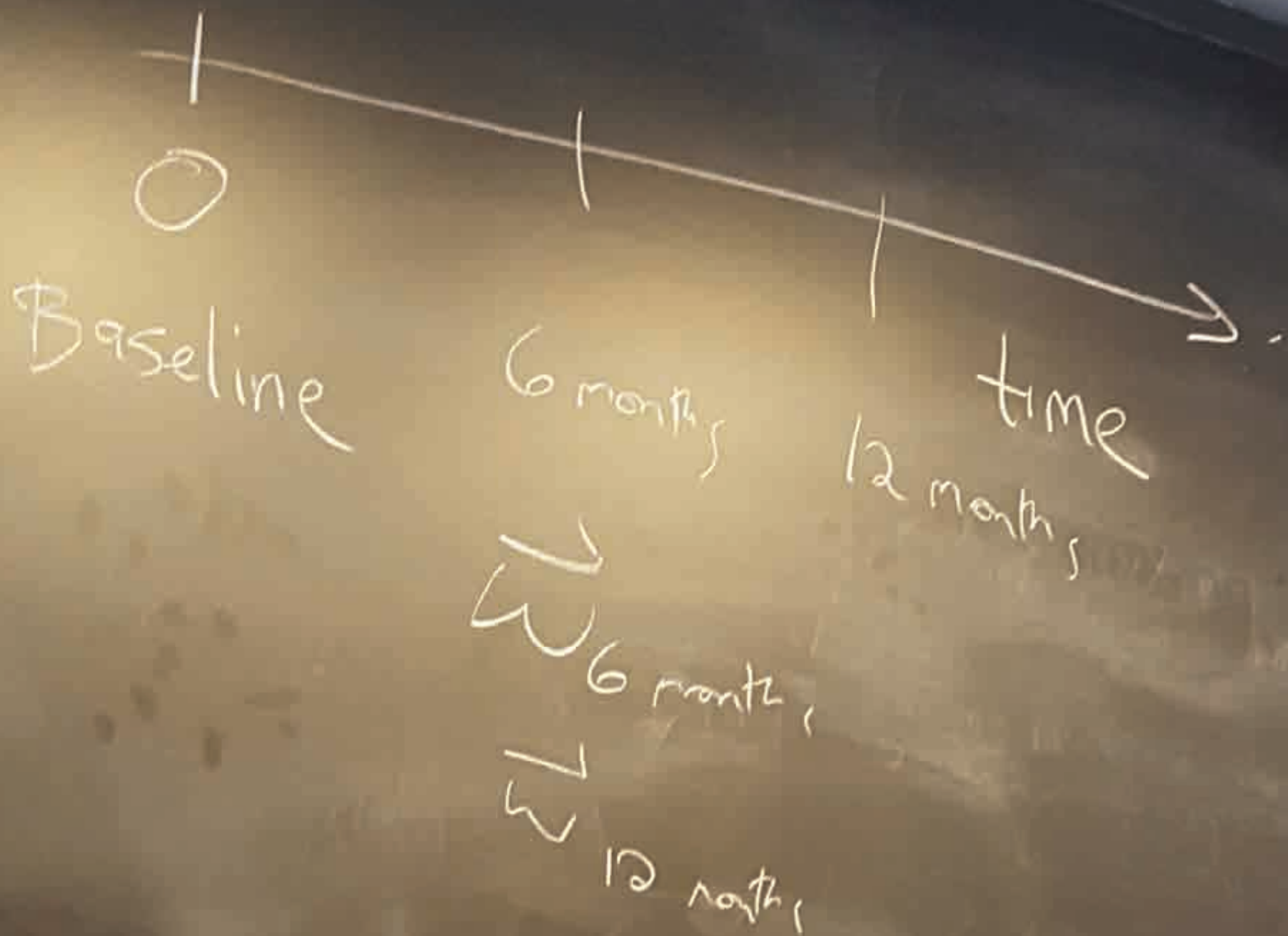
M06 = 6 months after baseline

[Zhou et al., KDD '12]

Multi-task learning

- Goal: Predict disease status in *6, 12, 24, 36, and 48 months*
- Rather than learn several independent models, view as *multi-task* learning
 - Select common set of biomarkers for all time points
 - Also allow for specific set of biomarkers at different time points
 - Incorporate temporal smoothness in models

[Zhou et al., KDD '12]



$$D_1 = \{ (\vec{x}, y) \mid \vec{w}, y \in \{0, 1\} \}$$

$$D_2 = \{ (\vec{x}, y) \mid \vec{w}_2$$

$k=1, 2$

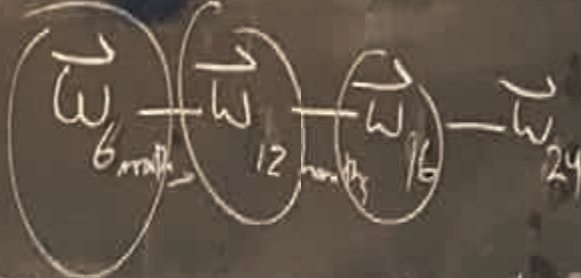
$$\min_{\vec{w}_k} \sum_{k \in D_k} \max(0, 1 - y_i \vec{x}_i \cdot \vec{w}_k) + \lambda \sum_k \|\vec{w}_k - \vec{w}_0\|^2$$

$\vec{w}_{16 \text{ months}}$

\vec{w}_0

$\vec{w}_{6 \text{ months}}$

$\vec{w}_{12 \text{ months}}$



$$\|\vec{w}_6 - \vec{w}_{12}\|_1 + \|\vec{w}_{12} - \vec{w}_{16}\|_1 + \|\vec{w}_{16} - \vec{w}_{24}\|_1$$

$$+ \sum_{(i,j) \in E} \lambda_{ij} \|\vec{w}_i - \vec{w}_j\|_2$$

Convex fused sparse group lasso

- Simultaneously learn all 5 models by solving the following convex optimization problem:

$$\min_W L(W) + \lambda_1 \|W\|_1 + \lambda_2 \|RW^T\|_1 + \lambda_3 \|W\|_{2,1}$$

- Squared loss: $L(W) = \|S \odot (XW - Y)\|_F^2$
(S is a mask to account for labels missing in subset of tasks)

- Group Lasso penalty $\|W\|_{2,1}$ given by $\sum_{i=1}^d \sqrt{\sum_{j=1}^t W_{ij}^2}$

- $R =$

			5
	1	-1	
		1	-1
4			1
			-1

[Zhou et al., KDD '12]

Features

MRI scans (white matter parcellation volume, etc.) +

Demographic	age, years of education, gender
Genetic	ApoE- ϵ 4 information
Baseline cognitive scores	MMSE, ADAS-Cog, ADAS-MOD, ADAS subscores, CDR, FAQ, GDS, Hachinski, Neuropsychological Battery, WMS-R Logical Memory
Lab tests	RCT1, RCT11, RCT12, RCT13, RCT14, RCT1407, RCT1408, RCT183, RCT19, RCT20, RCT29, RCT3, RCT392, RCT4, RCT5, RCT6, RCT8

371 in total

[Zhou et al., KDD '12]

Results (averaged over 5 time points)

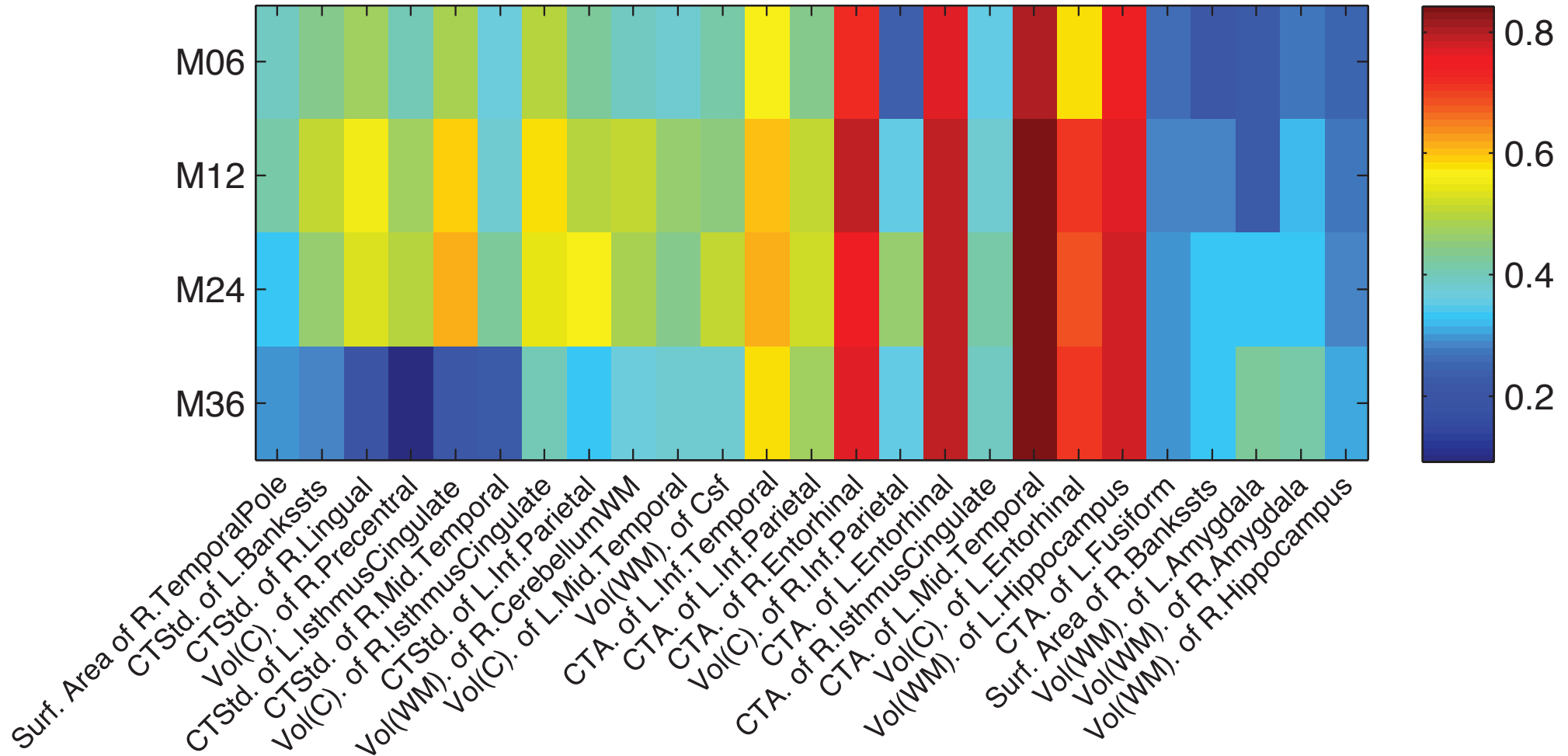
	Baseline – independent regressors	Temporal smoothing helps!		
		$\lambda_2 = 20$	$\lambda_2 = 50$	$\lambda_2 = 100$
	Ridge	cFSGL1	cFSGL2	cFSGL3
	Target: MMSE			
nMSE	0.548 ± 0.057	0.428 ± 0.052	0.400 ± 0.053	0.395 ± 0.052
R	0.689 ± 0.030	0.772 ± 0.030	0.790 ± 0.032	0.796 ± 0.031

nMSE – normalized mean squared error. Smaller is better

R – average R^2 (correlation coefficient). Larger is better

$$\min_W L(W) + \lambda_1 \|W\|_1 + \lambda_2 \|RW\|_1 + \lambda_3 \|W\|_{2,1}$$

Feature importance varies by time



(a) Target: ADAS-Cog (25 stable features)

Can we use an unsupervised approach?

- Twin goals:

- **Discover disease subtypes:**

Want to describe heterogeneity in a way that can be easy to act on (i.e., interpretable)

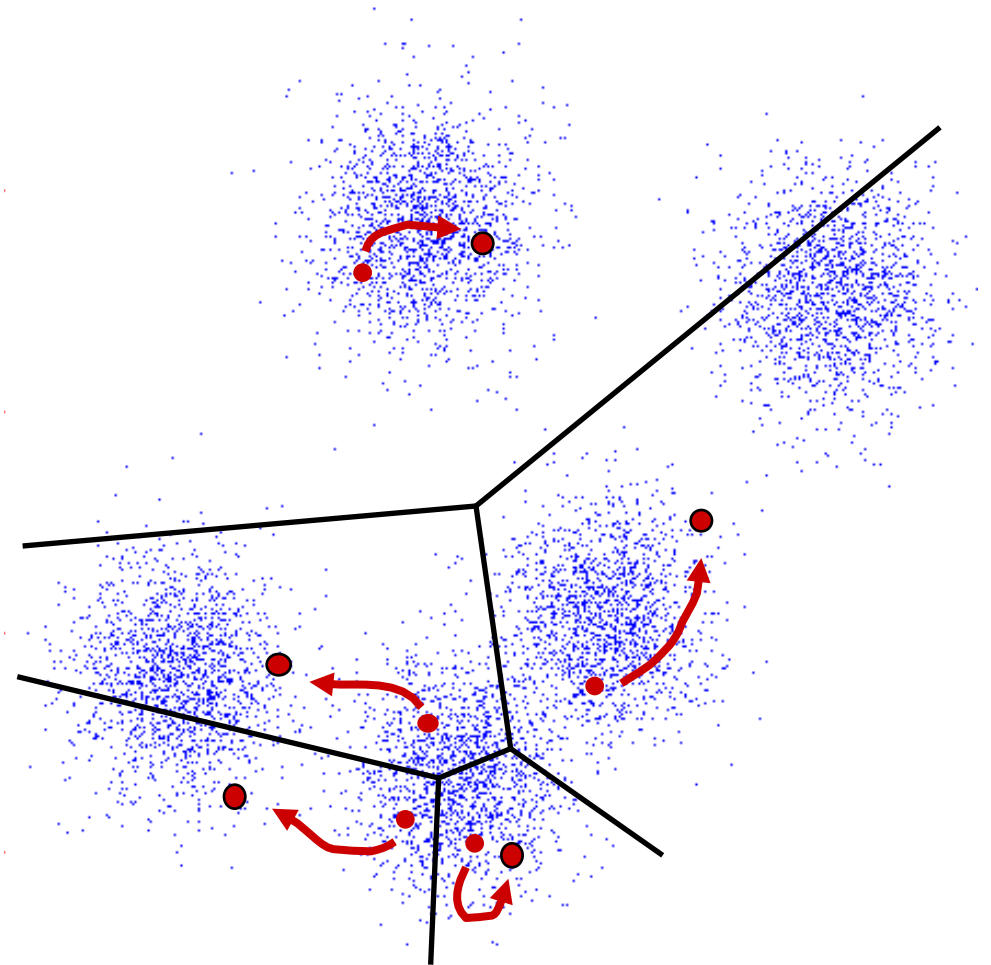
Not *just* interested in prediction – rather, identify cohorts for clinical trials, better understand disease mechanism

- **Make use of similarity of individuals at baseline**

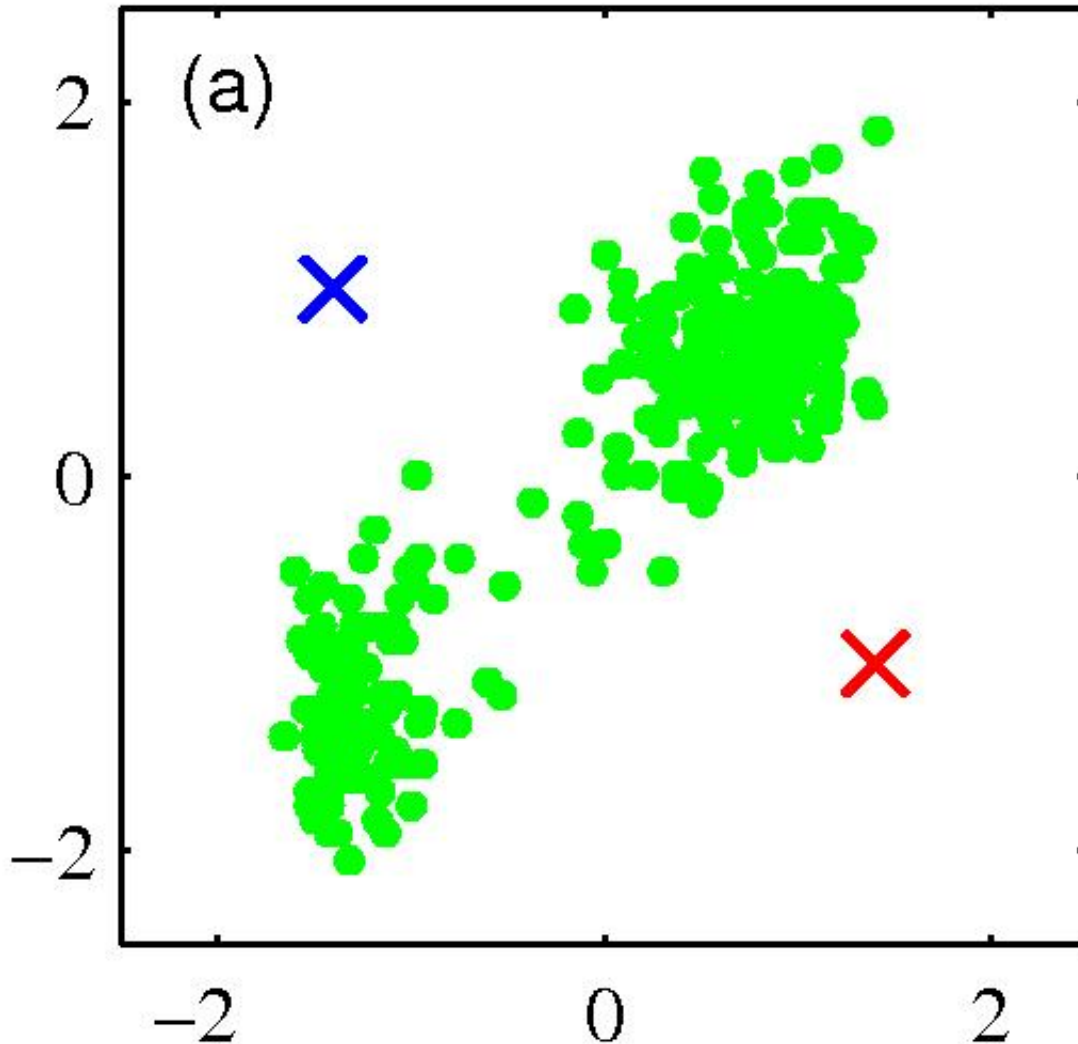
Dimensionality reduction to prevent overfitting

K-Means

- An iterative clustering algorithm
 - **Initialize:** Pick K random points as cluster centers
 - **Alternate:**
 1. Assign data points to closest cluster center
 2. Change the cluster center to the average of its assigned points
 - **Stop** when no points' assignments change



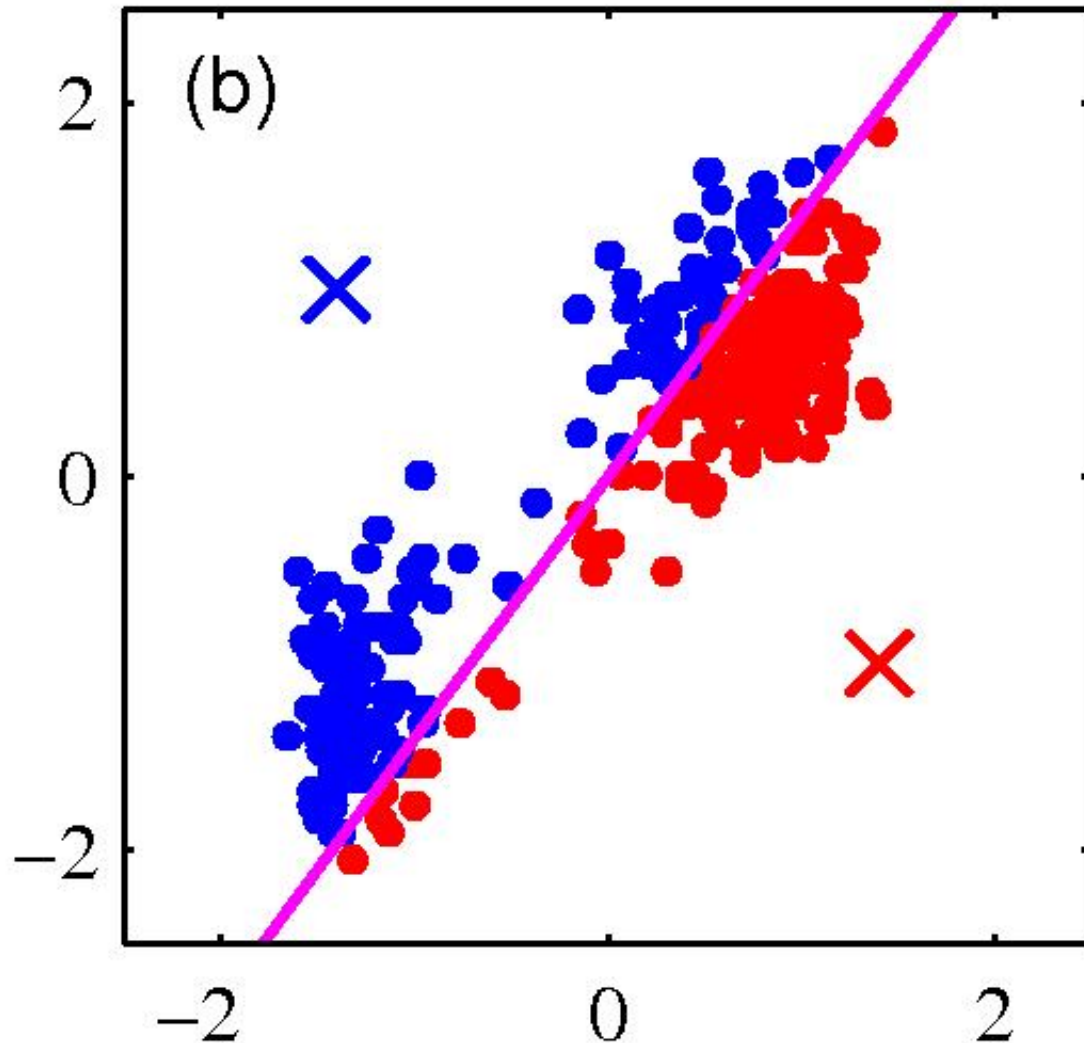
K-means clustering: Example



- Pick K random points as cluster centers (means)

Shown here for $K=2$

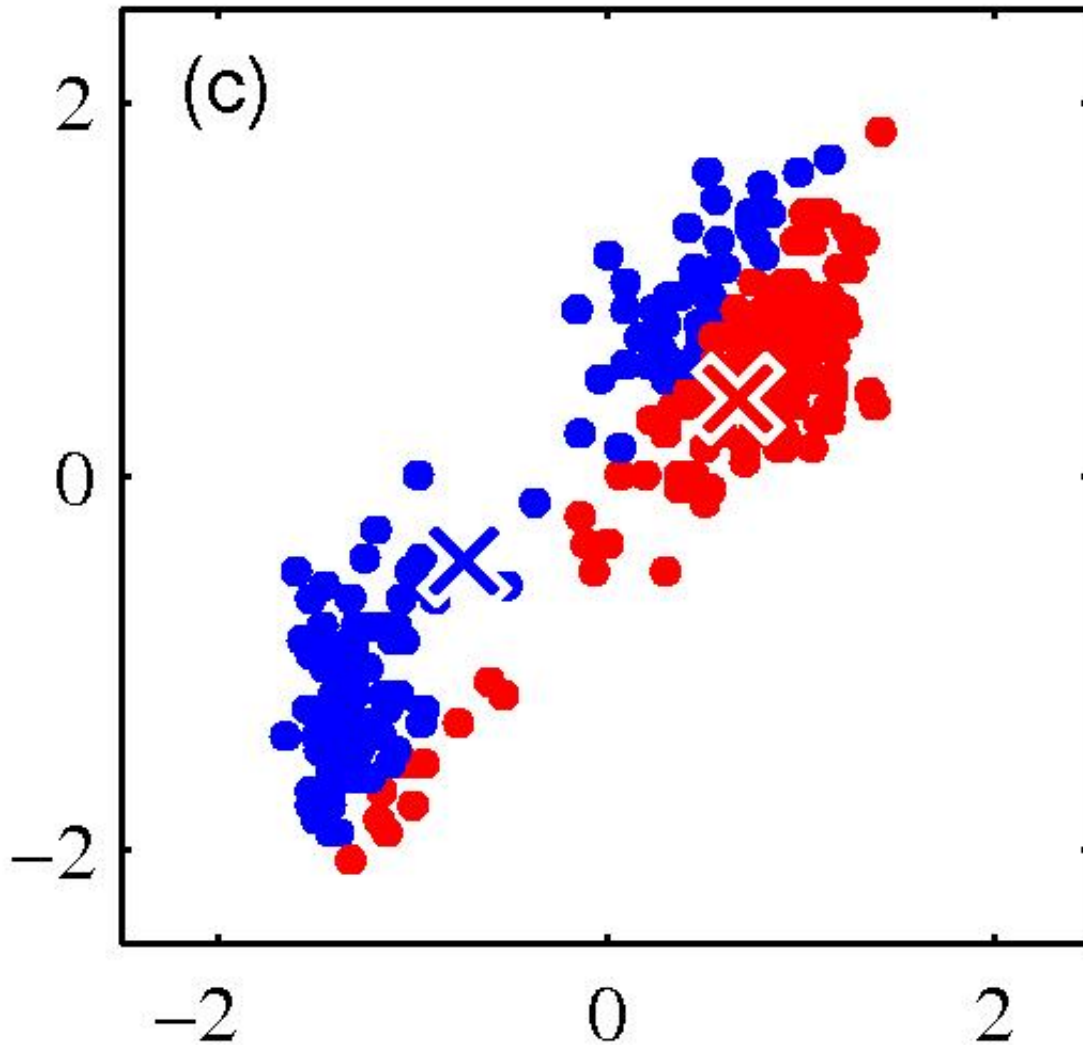
K-means clustering: Example



Iterative Step 1

- Assign data points to closest cluster center

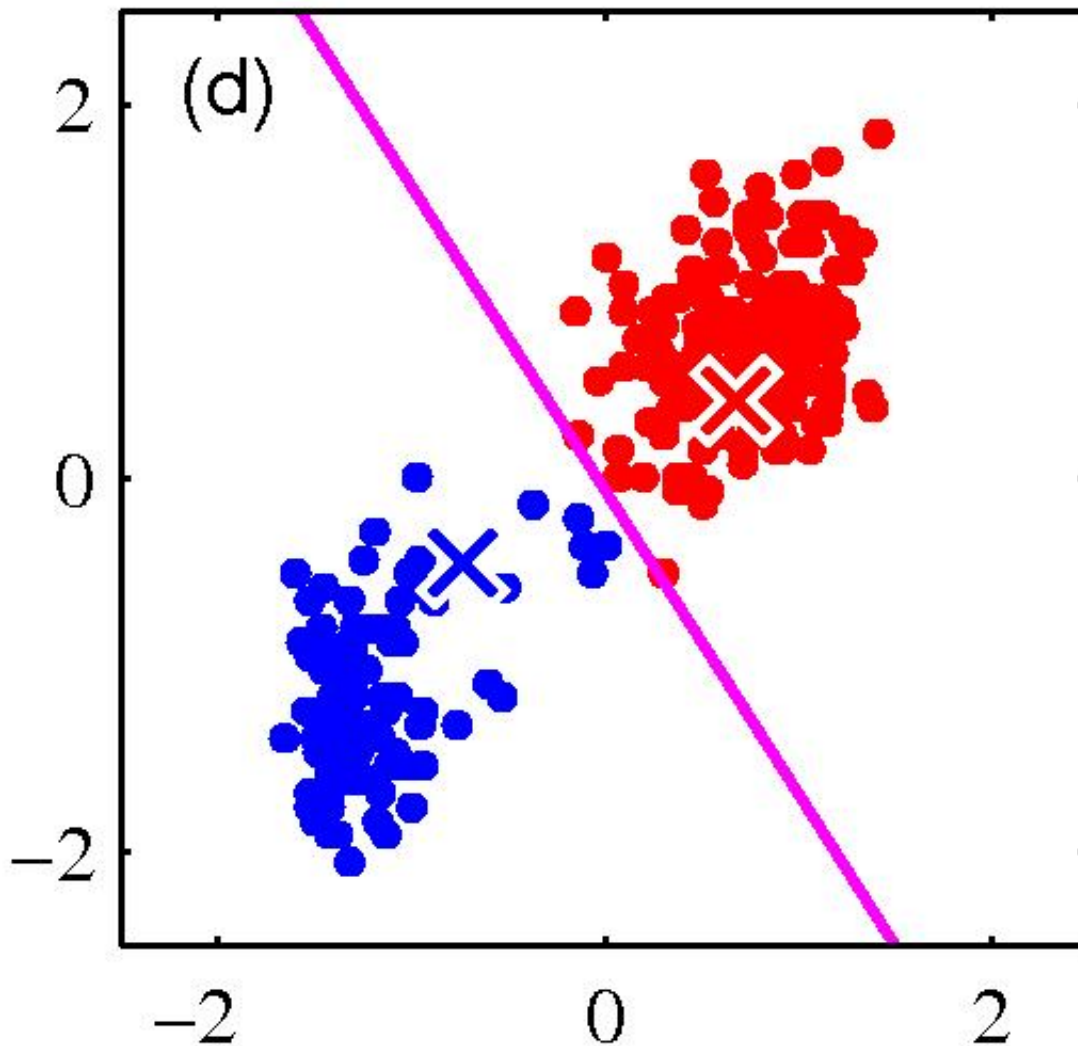
K-means clustering: Example



Iterative Step 2

- Change the cluster center to the average of the assigned points

K-means clustering: Example



- Repeat until convergence

Asthma: the problem

- 5 to 10% of people with severe asthma remain poorly controlled despite maximal inhaled therapy

[Holgate ST, Polosa R. The mechanisms, diagnosis, and management of severe asthma in adults. *Lancet*. 2006; 368:780–793]

Asthma: the question

“It is now recognised that there are distinct asthma phenotypes and that distinct therapeutic approaches may only impinge on some aspects of the disease process within each subgroup”

- What are the processes (genetic or environmental) that underlie different subtypes of asthma?
- Which aspects of airway remodelling are important in disease subtypes?
- What are the best biomarkers of disease progression or treatment response?
- Why are some patients less responsive to conventional therapies than others?

The data

- All patients had physician diagnosis of asthma and at least one recent prescription for asthma therapy
- All were current nonsmokers
- *Data set #1*: 184 patients recruited from primary-care practices in the UK
- *Data set #2*: 187 patients from refractory asthma clinic in the UK
- *Data set #3*: 68 patients from 12 month clinical study
- Features: z scores for continuous variables, 0/1 for categorical
 - Some of the continuous variables log-transformed to approximate a normal distribution

How should we treat asthma?

- Now we use 3rd dataset – 68 patients over 12 months
- Randomized control trial with two arms:
 - Standard clinical care (“clinical”)
 - Regular monitoring of airway inflammation using induced sputum, to titrate steroid therapy to maintain normal eosinophil counts (“sputum”)
- Original study found no difference in corticosteroid usage
 - But, this could have been explained by heterogeneity in treatment response!

Patients in different clusters respond differently to treatment! (analysis using 3rd dataset from 12 month study)

Cluster (found using <i>baseline</i> data)	Outcomes	Treatment strategy Study Group		Significance
		Clinical (<i>n</i> = 10)	Sputum (<i>n</i> = 8)	
1: Obese female	Δ Inhaled corticosteroid dose* /μg per day (SEM)	-400 (328)	-462 (271)	0.89
	Severe exacerbation frequency over 12 mo (SEM)	1.40 (0.78)	1.50 (0.80)	0.93
	Number commenced on oral corticosteroids	2	1	0.59
		Clinical (<i>n</i> = 15)	Sputum (<i>n</i> = 24)	
2: Inflammation predominant	Δ Inhaled corticosteroid dose* /μg per day (SEM)	+753 (334)	+241 (233)	0.22
	Severe exacerbation frequency over 12 mo (SEM)	3.53 (1.18)	0.38 (0.13)	0.002
	Number commenced on oral corticosteroids	2	9	0.17
		Clinical (<i>n</i> = 7)	Sputum (<i>n</i> = 4)	
3: Early symptom predominant	Δ Inhaled corticosteroid dose* /μg per day (SEM)	+1,429 (429)	-400 (469)	0.022
	Severe exacerbation frequency over 12 mo (SEM)	5.43 (1.90)	2.50 (0.87)	0.198
	Number commenced on oral corticosteroids	6	0	Undefined

[Haldar et al., *Am J Respir Crit Care Med*, 2008]

Summary – two approaches

- **Supervised:**
predict future disease status
- **Unsupervised:**
which patients look similar / different? Do clusters have different outcomes?

Limitations that we'll address in the next lecture

- Can't differentiate between *stage* and *subtype*
 - Patients assumed to be aligned at baseline
- Only make use of one time point per patient
- Assumes single factor (cluster) explains all variation
- Distance function is particularly simplistic
- Either supervised or unsupervised, but not both – how to combine?

MIT OpenCourseWare

<https://ocw.mit.edu>

6.S897 / HST.956 Machine Learning for Healthcare

Spring 2019

For information about citing these materials or our Terms of Use, visit: <https://ocw.mit.edu/terms>