



**POLITECNICO**  
MILANO 1863

# Is Dementia predictable?

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## Dataset Dementia and Alzheimer longitudinal

Subject.ID	MRI.ID	Group	Visit	MR.Delay	M.F	Hand	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14	2	27	0.0	1987	0.696	0.883
OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2	30	0.0	2004	0.681	0.876
OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12	NA	23	0.5	1678	0.736	1.046
OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12	NA	28	0.5	1738	0.713	1.010
OAS2_0002	OAS2_0002_MR3	Demented	3	1895	M	R	80	12	NA	22	0.5	1698	0.701	1.034
OAS2_0004	OAS2_0004_MR1	Nondemented	1	0	F	R	88	18	3	28	0.0	1215	0.710	1.444
OAS2_0004	OAS2_0004_MR2	Nondemented	2	538	F	R	90	18	3	27	0.0	1200	0.718	1.462
OAS2_0005	OAS2_0005_MR1	Nondemented	1	0	M	R	80	12	4	28	0.0	1689	0.712	1.039
OAS2_0005	OAS2_0005_MR2	Nondemented	2	1010	M	R	83	12	4	29	0.5	1701	0.711	1.032

where SES is Socioeconomic Status, MMSE is Mini Mental State Examination, CDR is Clinical Dementia Rating, eTIV is Estimated Total Intracranial Volume, nWBV is Normalize Whole Brain Volume and ASF is Atlas Scaling Factor.

Source: Kaggle

# Analysis Male VS Female

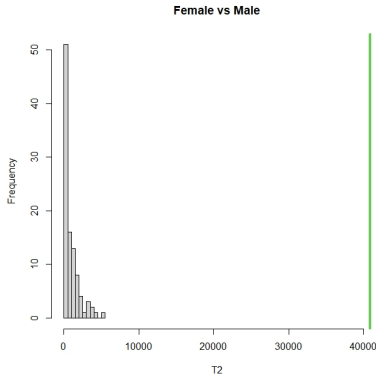
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Variable considered: [Age, EDUC, MMSE, eTIV, nWBV, ASF]

$$H_0 : Y_{female} \stackrel{d}{=} Y_{male} \text{ vs } H_1 : Y_{female} \stackrel{d}{\neq} Y_{male}$$

$$T_0 = |\bar{Y}_{female} - \bar{Y}_{male}|$$

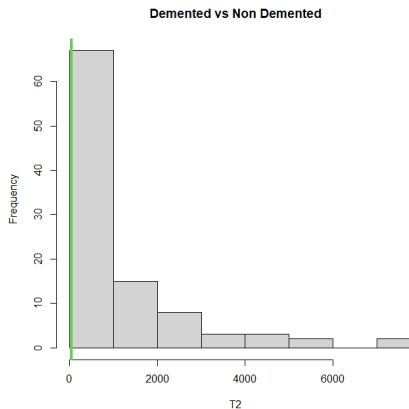
$$pvalue = 0$$



# Demented VS Nondemented

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$$H_0 : \mathbf{Y}_{Demented} \stackrel{d}{=} \mathbf{Y}_{NonDemented} \text{ vs } H_1 : \mathbf{Y}_{Demented} \stackrel{d}{\neq} \mathbf{Y}_{NonDemented}$$

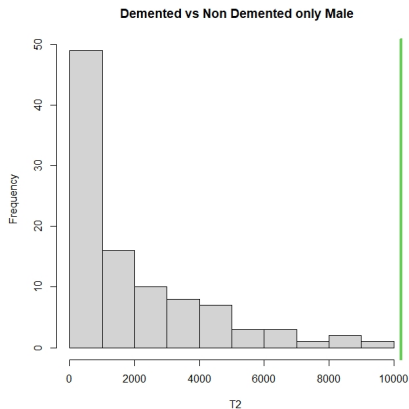


$pvalue = 0.9$

# Demented VS Nondemented only Male

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$$H_0 : M_{Demented} \stackrel{d}{=} M_{NonDemented} \text{ vs } H_1 : M_{Demented} \stackrel{d}{\neq} M_{NonDemented}$$

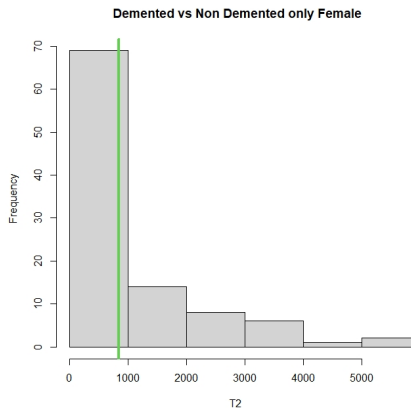


$pvalue = 0$

# Demented VS Nondemented only Female

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$$H_0 : F_{Demented} \stackrel{d}{=} F_{NonDemented} \text{ vs } H_1 : F_{Demented} \stackrel{d}{\neq} F_{NonDemented}$$



$pvalue = 0.37$

$$EDUC = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon$$

$j = \{male, female\}$  ,  $i = \{Demented, NonDemented\}$

$\alpha = sex$ ,  $\beta = diagnostic$ ,  $\gamma = interaction$

$$H_0 : \gamma_{ij} = 0 \text{ vs } H_1 : \gamma_{ij} \neq 0$$

TEST STATISTIC:  $T0 = F - STATISTICS$

$p - value = 0.082$  at level of confidence 95% there's no evidence to reject  $H_0$ , so we reduce the model



$$EDUC = \mu + \alpha_i + \beta_j + \epsilon$$

$$H_0 : \beta_j = 0 \text{ vs } H_1 : \beta_j \neq 0$$

$p - \text{value} = 0.069$  at level of confidence 95% there's no evidence to reject  $H_0$

$$EDUC = \mu + \alpha_i$$

$$H_0 : \alpha_i = 0 \text{ vs } H_1 : \alpha_i \neq 0$$

$p - \text{value} = 0.08$  we could say that's neither of the grouping is significant at 95%

while with parametric test at least the diagnostic division is significant

$$MMSE = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon$$

$$j = \{male, female\}, i = \{Demented, NonDemented\}$$

$$H_0 : \gamma_{ij} = 0 \text{ vs } H_1 : \gamma_{ij} \neq 0$$

TEST STATISTIC:  $T0 = F - STATISTICS$

$p - value = 0.875$

there's no evidence to reject  $H_0$ , so we reduce the model

$$EDUC = \mu + \alpha_i + \beta_j + \epsilon$$

$$H_0 : \beta_j = 0 \text{ vs } H_1 : \beta_j \neq 0$$

$p - \text{value} = 0.446$  there's no evidence to reject  $H_0$

$$EDUC = \mu + \alpha_i$$

$$H_0 : \alpha_i = 0 \text{ vs } H_1 : \alpha_i \neq 0$$

$p - \text{value} = 0$  there's evidence to reject  $H_0$  so the most significative model is  $MMSE \sim \text{Diagnostic}$  where Diagnostic is the division between Demented and Non Demented

Used a logistic model of classification Demented-Nondemented, with smoothing splines (degree 3) for EDUC, nWBV, Age, MMSE

$$\log \frac{p}{1-p} = EDUC + nWBV + Age + MMSE + CDR$$

with  $p$  = probability that the observation is 'Demented'

```
Shapiro-Wilk normality test
```

```
data: model_gam$residuals  
W = 0.93137, p-value = 2.796e-11
```

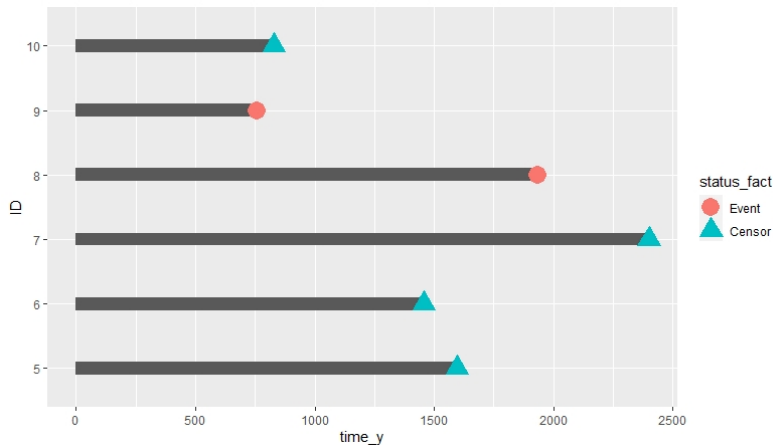
## Prediction for Converted patients:

```
> options(scipen = 100, digits = 7)
> pred
      34      35      36      37      38      39      58      59      60
pred 0.05316856 0.09237775 0.674794 0.05863945 0.6125401 0.8149156 0.08133388 0.06052873 0.6179306
      82      83      84      115      116      195      196      219      220
pred 0.2627466 0.143016 0.6089418 0.07991747 0.8438092 0.1722836 0.7792069 0.08776355 0.5495934
      221      246      247      262      263      264      265      266      272
pred 0.5288126 0.04125604 0.8154823 0.0546213 0.5348506 0.5376504 0.5582587 0.5111782 0.6304302
      273      274      275      296      297      298      299      347      348
pred 0.4895987 0.1248788 0.6994842 0.05183226 0.5211393 -0.00002013915 0.5363979 0.04796561 0.04393508
      349
pred 0.4964958
\ |
```

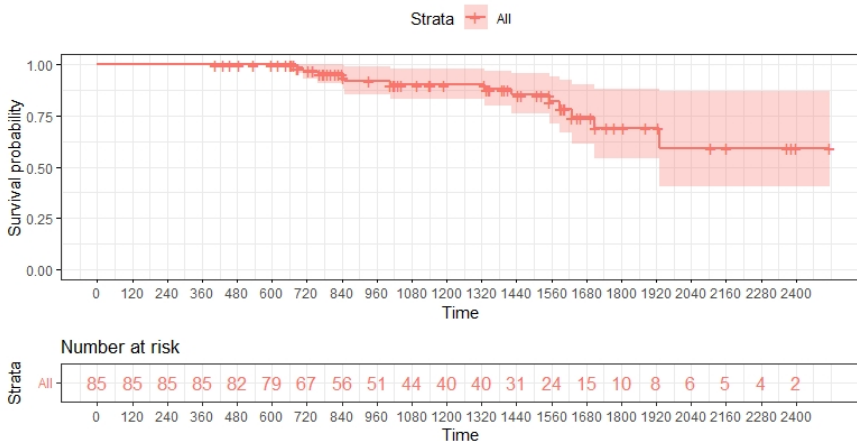
## Prediction for Nondemented patients:

```
      1      2      6      7      8      9
0.33197223 0.08501153 0.16418897 0.21870711 0.23499001 0.64639607
      10      20      21      22      23      24
0.12727284 0.06378905 0.08046988 0.12099097 0.10163539 0.10233746
      25
0.18136779
```

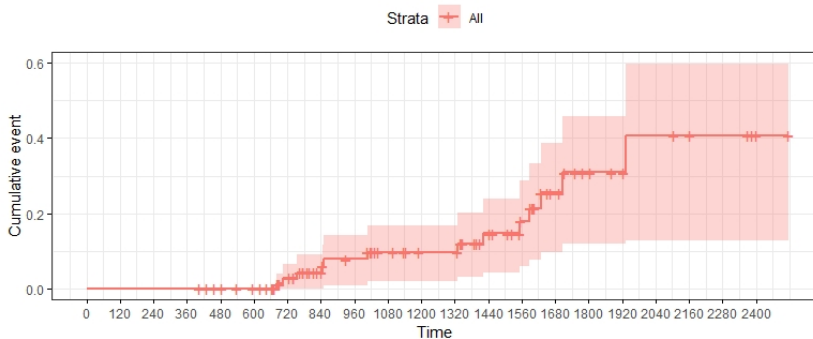
Event: disease occurred



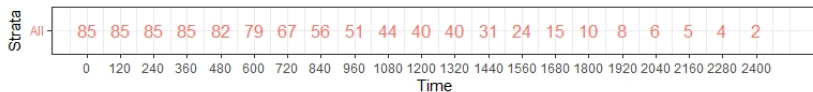
Kaplan-Meier Curve for Dementia Survival



Cumulative Incidence Curve for Dementia Survival



Number at risk

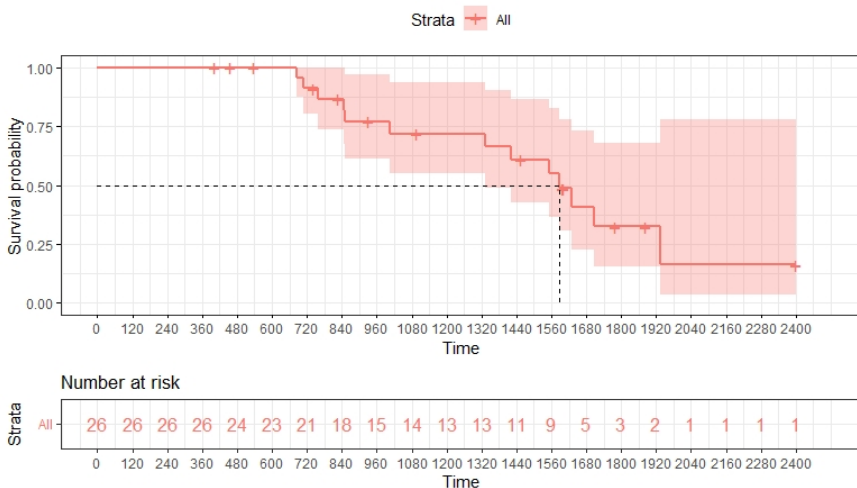




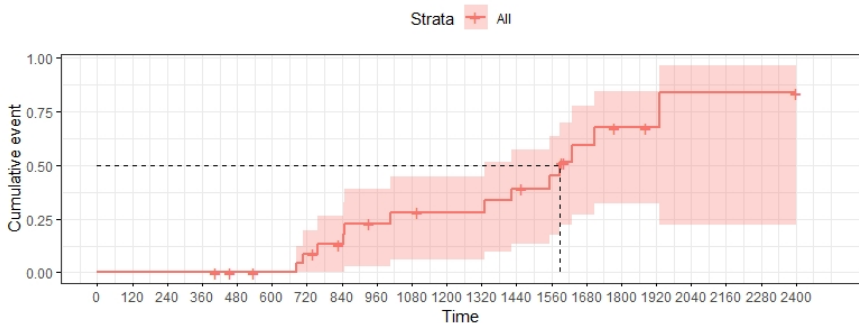
# Survival Analysis - Balanced (I)

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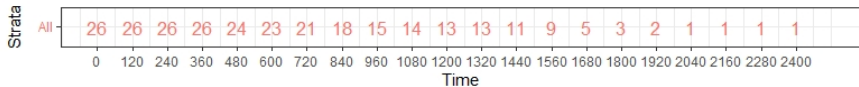
Kaplan-Meier Curve for Dementia Survival



Cumulative Incidence Curve for Dementia Survival



Number at risk



- Complete our survival analysis
- Solve the residual gaussianity problem
- Perform a prediction on the other dataset of patient (not labelled)