Is Dementia predictable?

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Dataset

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

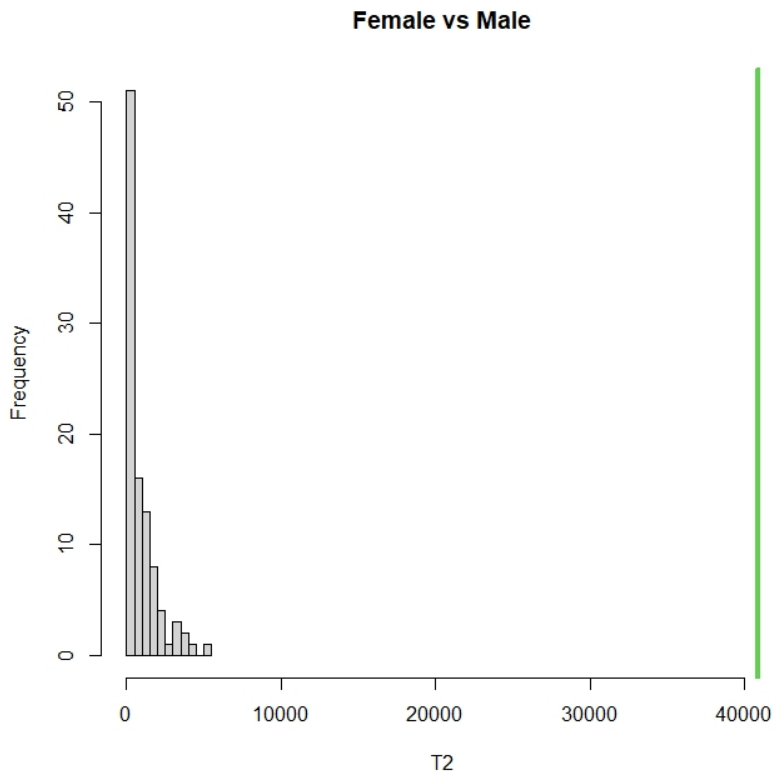
Analysis Male VS Female

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

$$H_0 : \mathbf{Y}_{female} \stackrel{d}{=} \mathbf{Y}_{male} \; vs \; H_1 : \mathbf{Y}_{female} \stackrel{d}{\neq} \mathbf{Y}_{male}$$

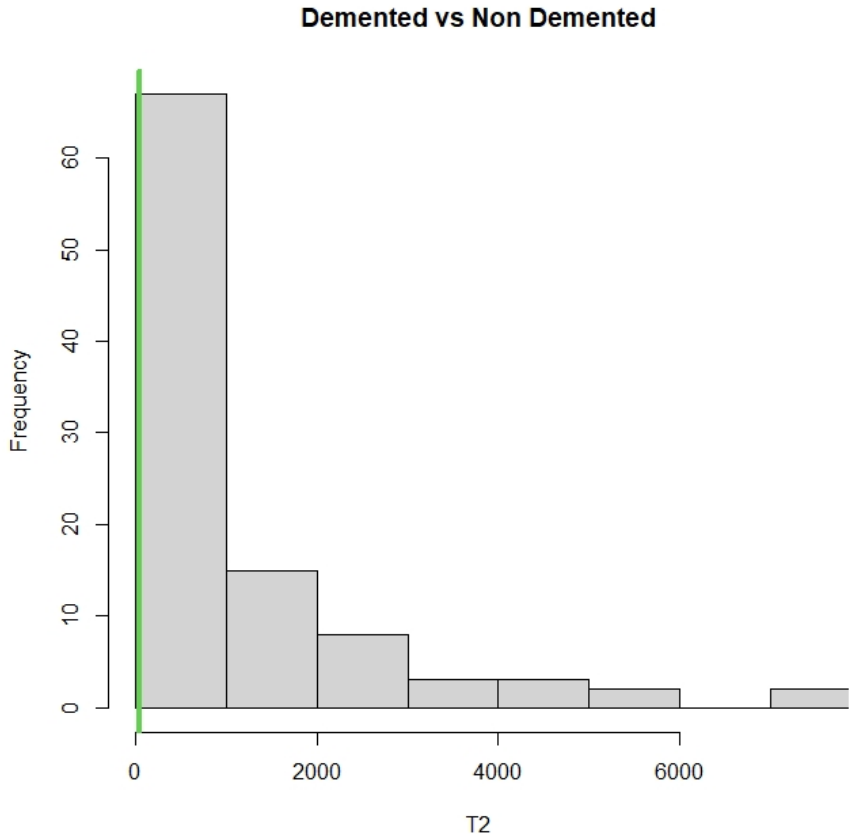
$$T_0 = |\bar{Y}_{female} - \bar{Y}_{male}|$$

$$pvalue = 0$$



Demented VS Nondemented

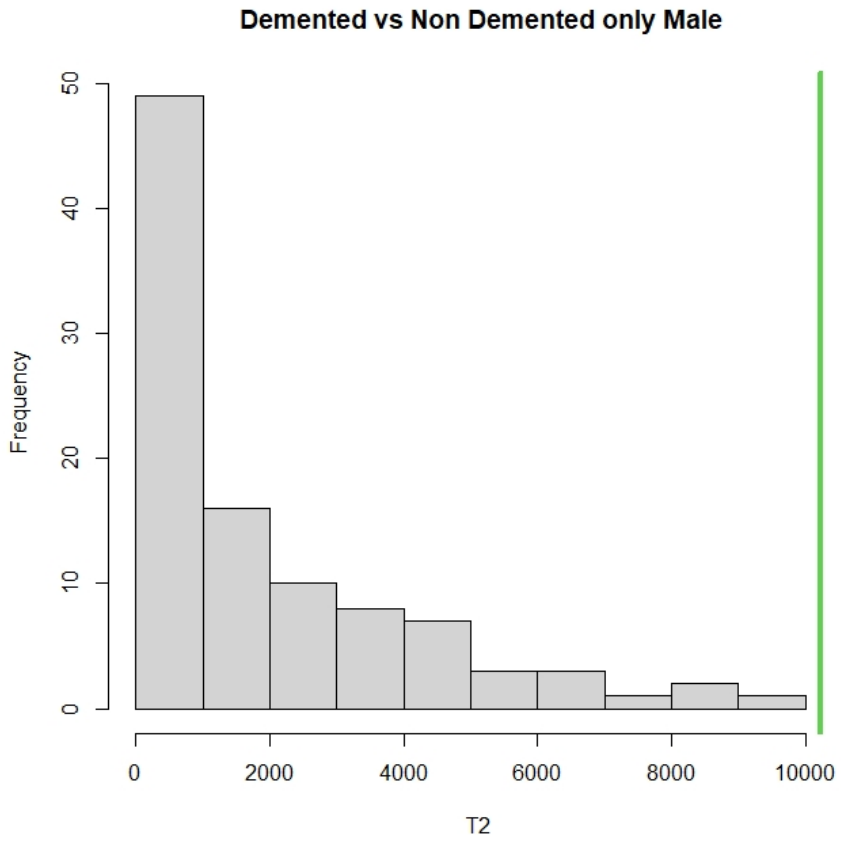
$$H_0 : \mathbf{Y}_{Demented} \overset{d}{=} \mathbf{Y}_{NonDemented} \ vs \ H_1 : \mathbf{Y}_{Demented} \overset{d}{\neq} \mathbf{Y}_{NonDemented}$$



$pvalue = 0.9$

Demented VS Nondemented only Male

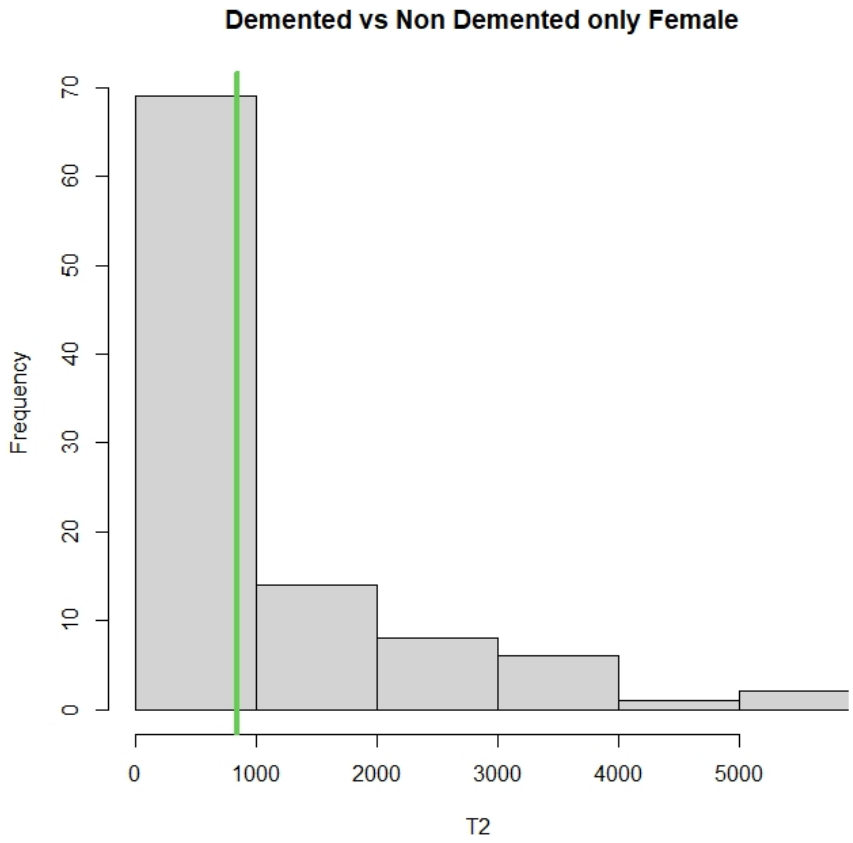
$$H_0 : \mathbf{M}_{Demented} \overset{d}{=} \mathbf{M}_{NonDemented} \ vs \ H_1 : \mathbf{M}_{Demented} \overset{d}{\neq} \mathbf{M}_{NonDemented}$$



$pvalue = 0$

Demented VS Nondemented only Female

$$H_0 : \mathbf{F}_{Demented} \overset{d}{=} \mathbf{F}_{NonDemented} \ vs \ H_1 : \mathbf{F}_{Demented} \overset{d}{\neq} \mathbf{F}_{NonDemented}$$



$pvalue = 0.37$

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

$i = \{male, female\}$, $j = \{Demented, NonDemented\}$
$\alpha = sex$, $\beta = diagnostic$, $\gamma = interaction$

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

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

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

$$H_0 : \beta_j = 0 \ \ vs \ H_1 : \beta_i \neq 0$$

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

$$EDUC = \mu + \alpha_i$$

$$H_0 : \alpha_i = 0 \ \ vs \ H_1 : \alpha_i \neq 0$$

$p - value = 0.08$ we could say that's neither of the grouping is significant at 95%
while with parametric test at least the diagnostic division is significant

TWO WAYS ANOVA: MMSE (I)

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

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

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

TEST STATISTIC: $T0 = F - STATISTICS \quad p - value = 0.875$ there's no evidence to reject H_0 so we reduce the model

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

$$H_0 : \beta_j = 0 \ \ vs \ H_1 : \beta_j \neq 0$$

$p - value = 0.446$ there's no evidence to reject H_0

$$EDUC = \mu + \alpha_i$$

$$H_0 : \alpha_i = 0 \ \ vs \ H_1 : \alpha_i \neq 0$$

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

Regression

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

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

```
        Shapiro-Wilk normality test

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

```
Family: gaussian
Link function: identity

Formula:
I(Group == "Demented") ~ s(EDUC, bs = "cr") + s(nWBV,
    bs = "cr") + s(Age, bs = "cr") + s(MMSE, bs = "cr") +
    CDR

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.15618    0.01869   8.354 2.04e-15 ***
CDR          0.94676    0.04880  19.401  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
           edf Ref.df     F  p-value
s(EDUC) 0.8448      4 1.883 0.002764 **
s(nWBV) 1.7831      9 1.137 0.002050 **
s(Age)  4.2328      9 2.338 0.000138 ***
s(MMSE) 5.6855      9 8.571 2.03e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.798   Deviance explained = 80.6%
GCV = 0.051899  Scale est. = 0.049638  n = 334
```

Prediction

Prediction for Demented patients:

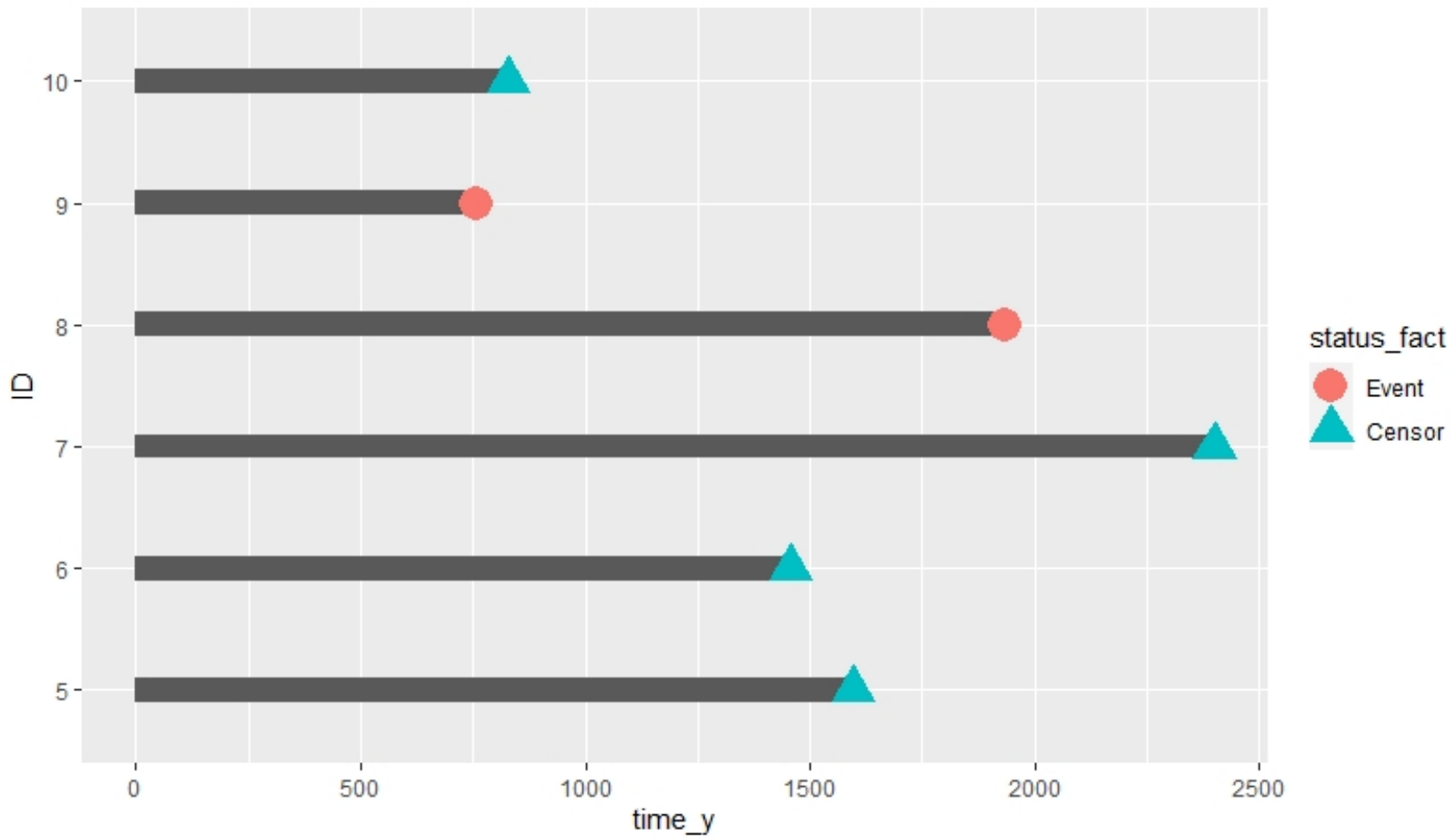
```
> options(scipen = 100, digits = 7)
> pred
            34         35       36         37        38        39         58         59        60
pred 0.05316856 0.09237775 0.674794 0.05863945 0.6125401 0.8149156 0.08133388 0.06052873 0.6179306
            82       83        84        115       116       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:

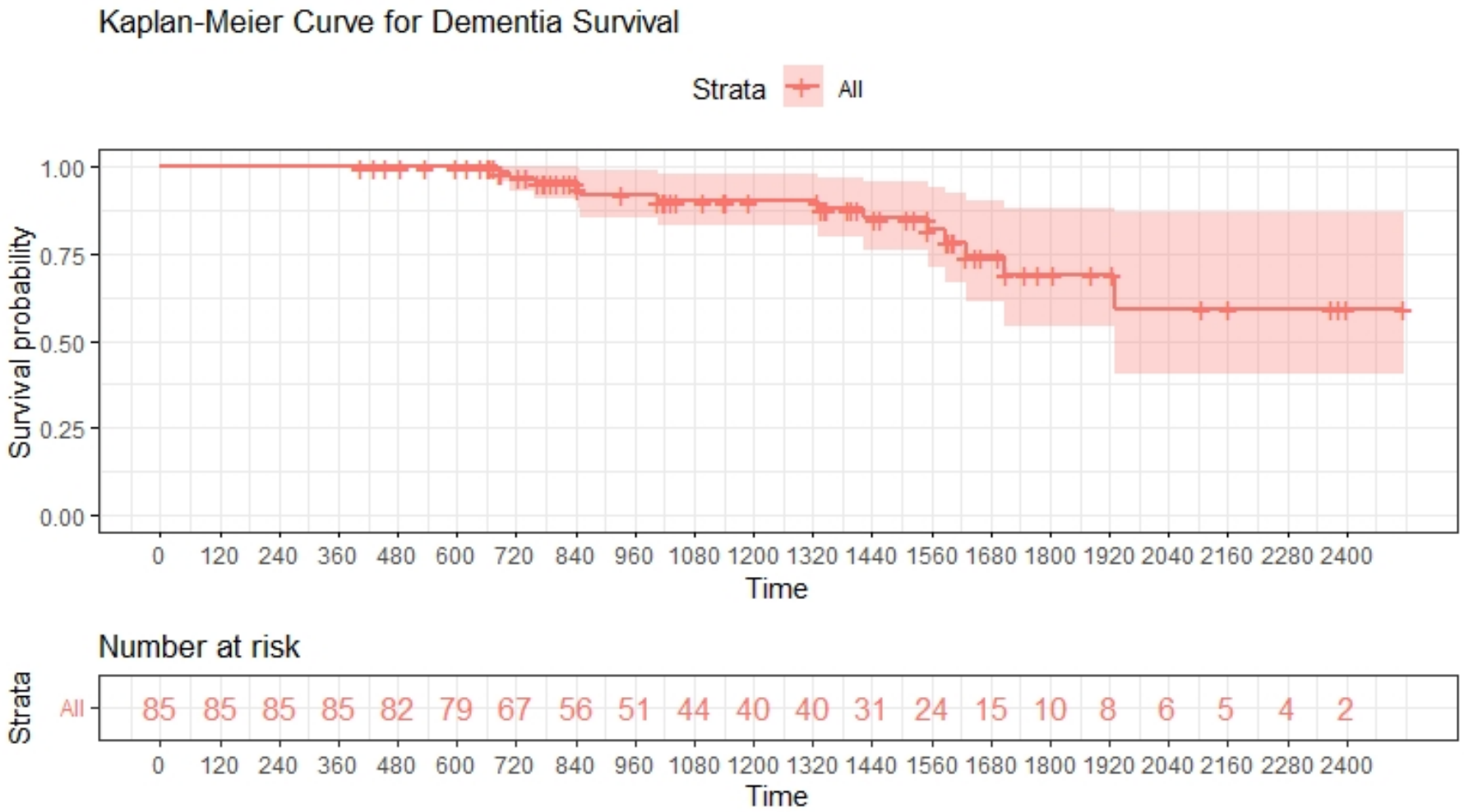
```
        1         2         6         7         8         9
0.33197223 0.08501153 0.16418897 0.21870711 0.23499001 0.64639607
       10        20        21        22        23        24
0.12727284 0.06378905 0.08046988 0.12099097 0.10163539 0.10233746
       25
0.18136779
```

Survival Analysis (I)

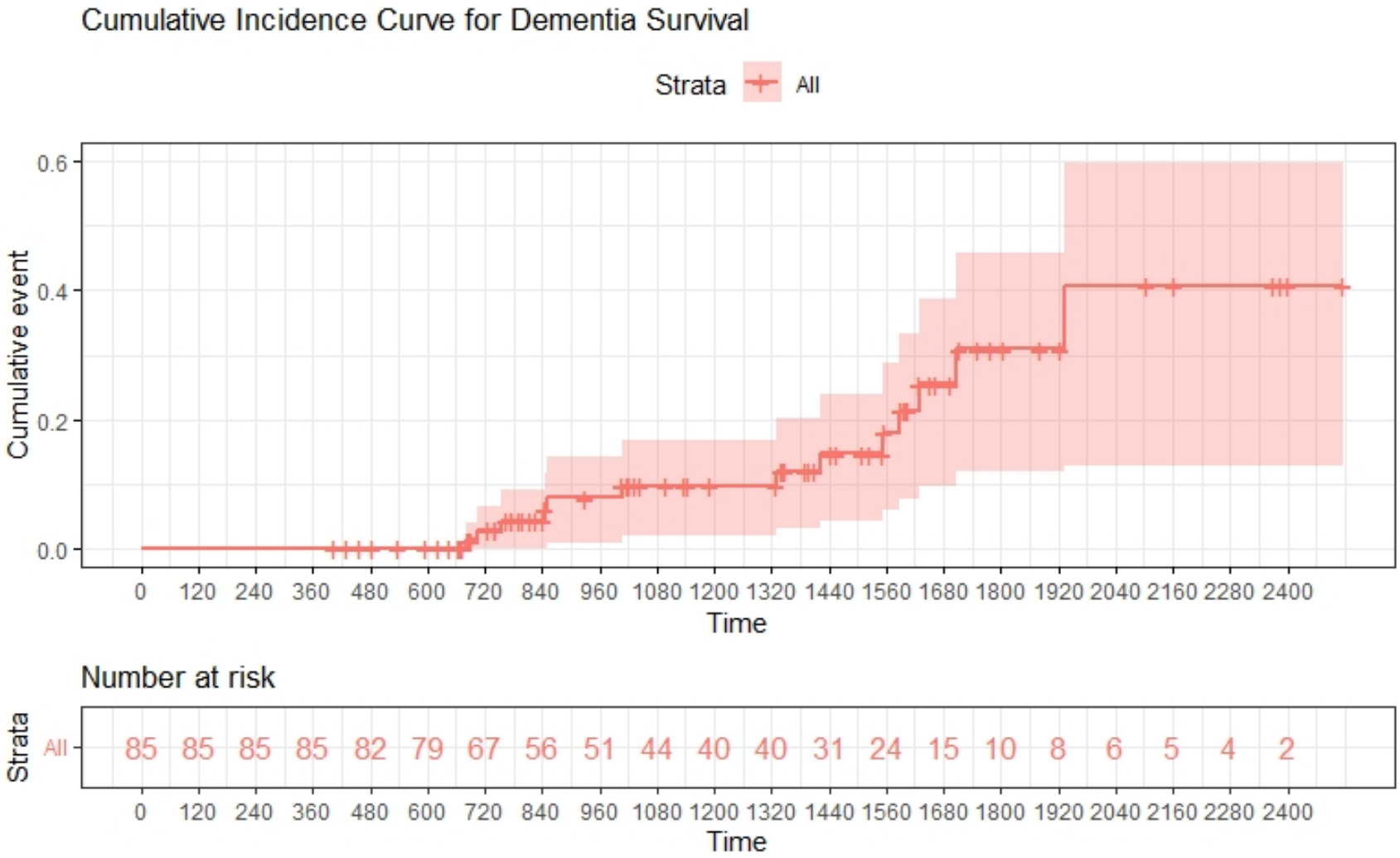
Event: disease occurred



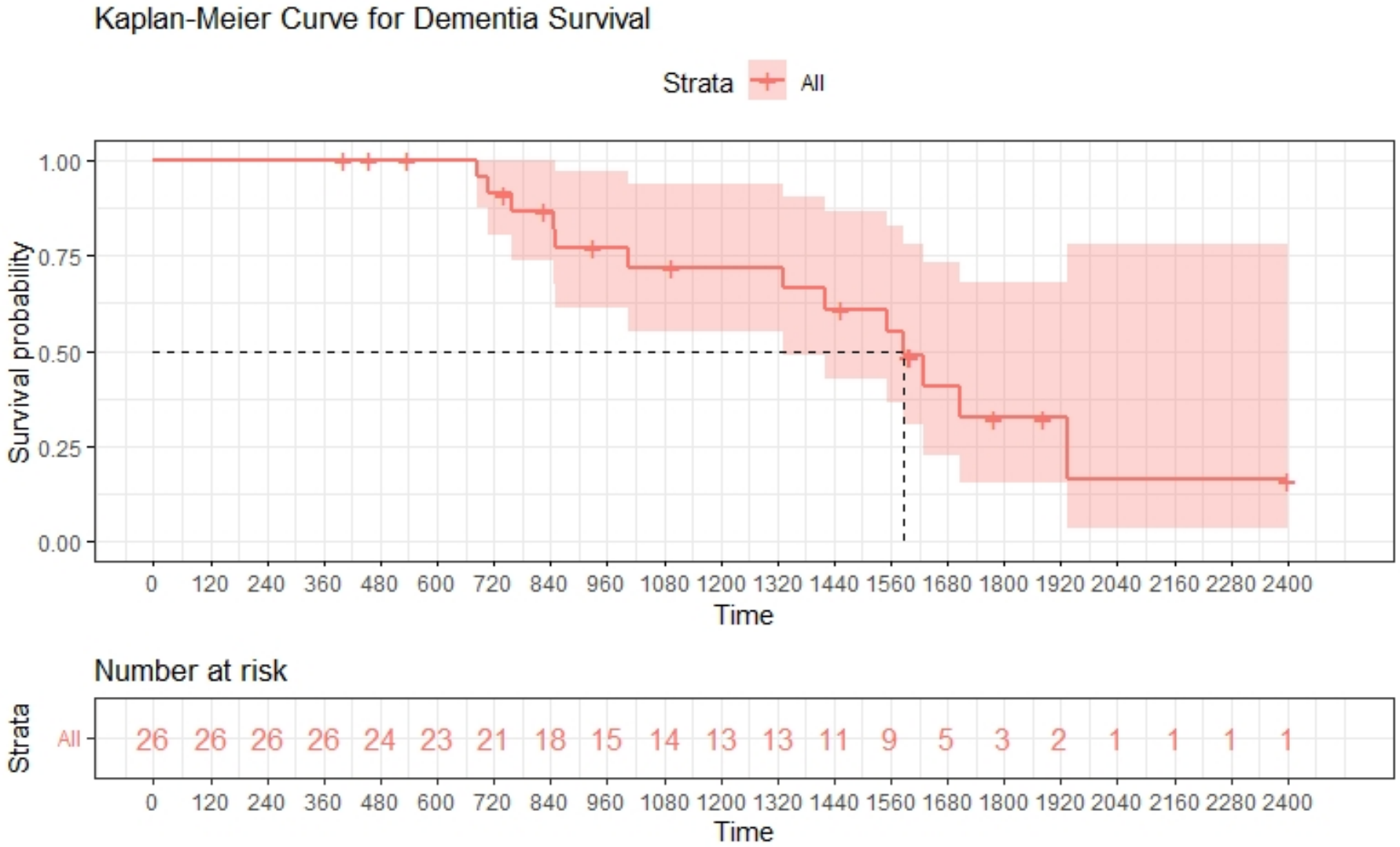
Survival Analysis (II)



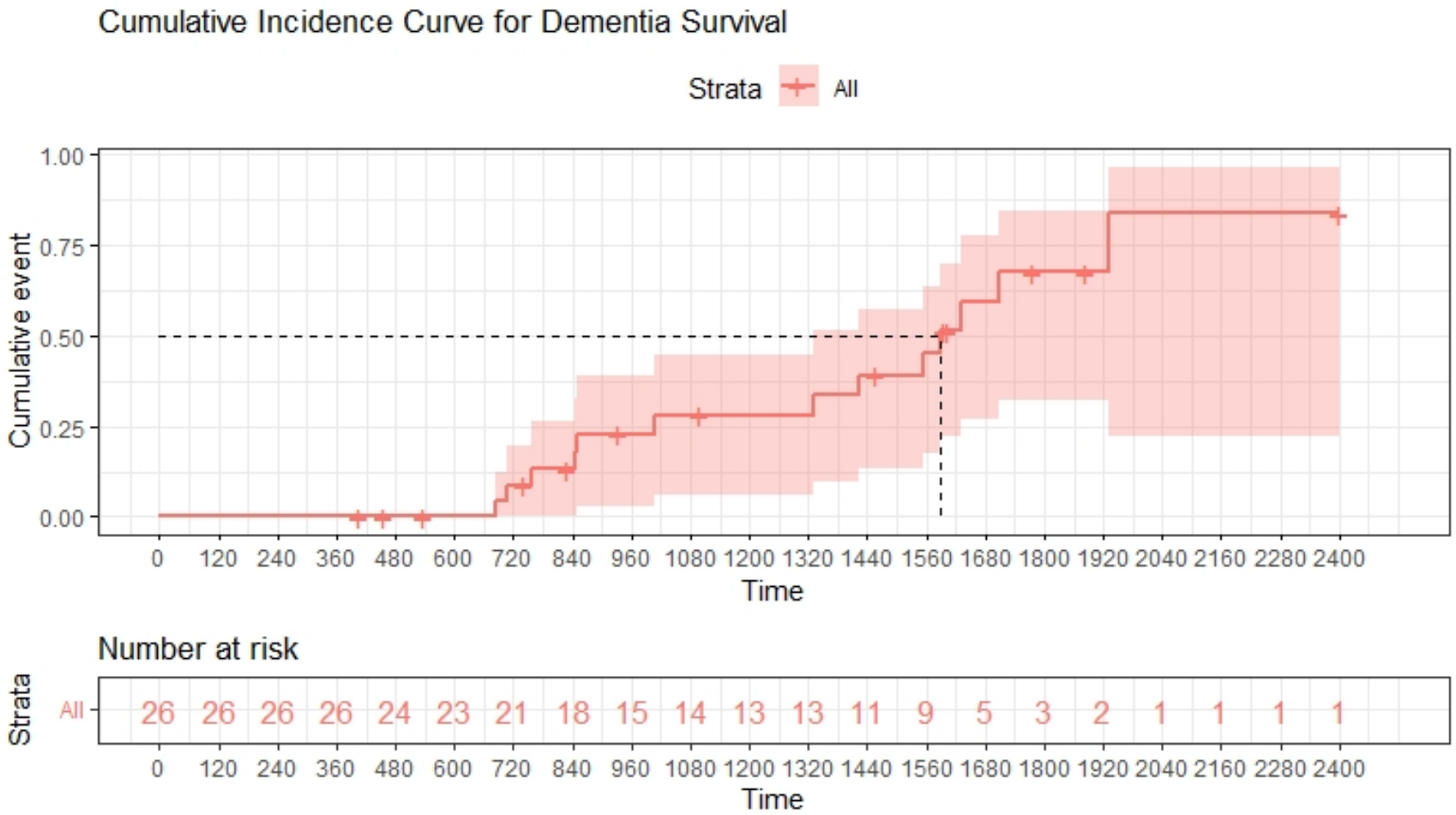
Survival Analysis(III)



Survival Analysis - Balanced (I)



Survival Analysis - Balanced (II)



Future goals

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