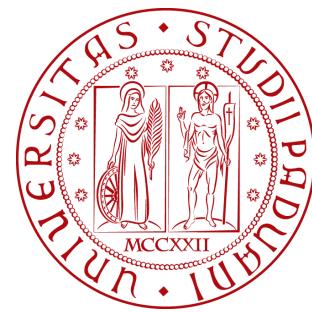


# Are we getting interactions wrong? The role of link functions in psychological research



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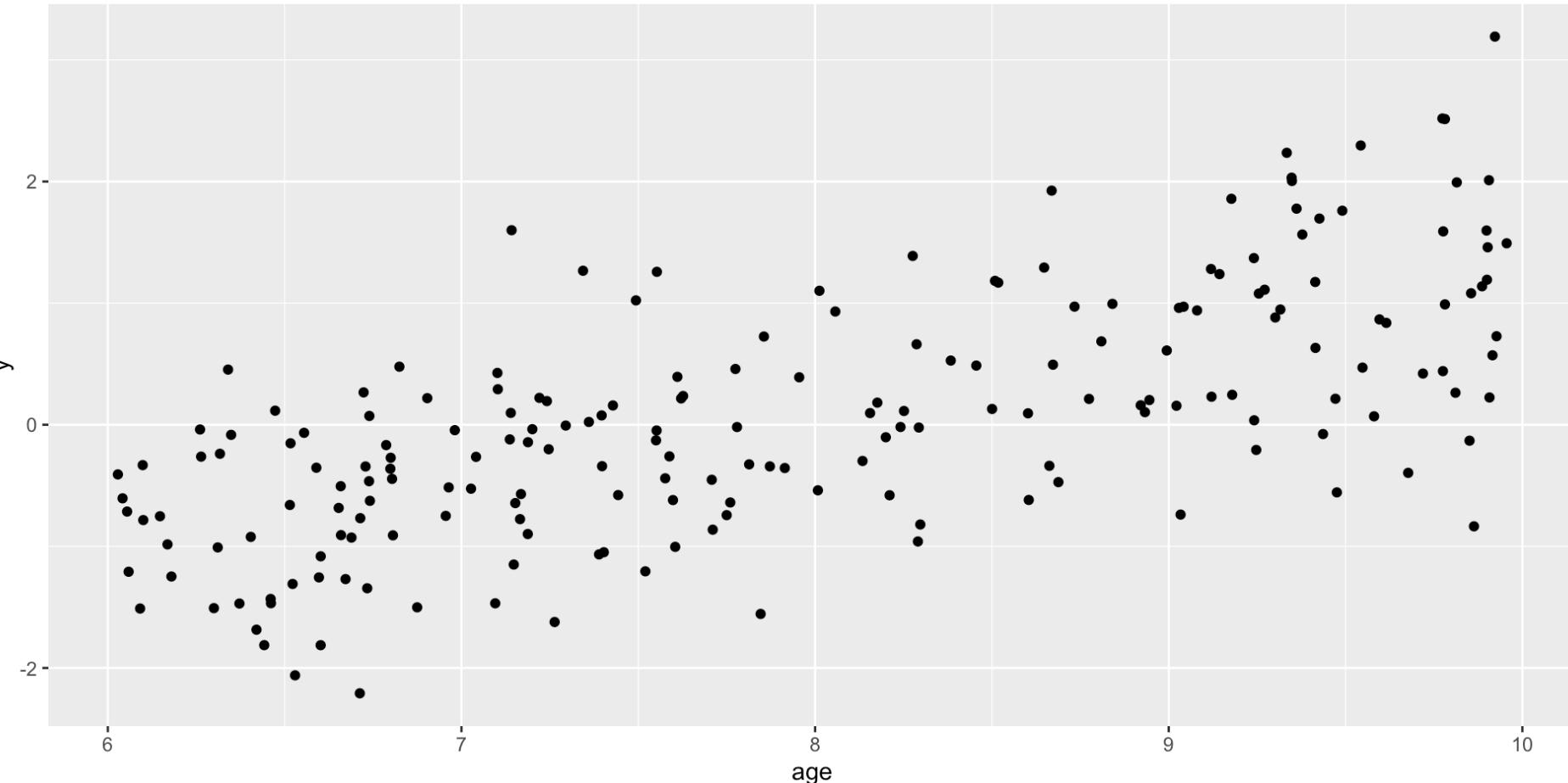
Laura Sità, Margherita Calderan, Tommaso Feraco,  
Filippo Gambarota, Enrico Toffalini

# 1 Example

# Simulated dataset 1

independent variable: age in years ([years](#))

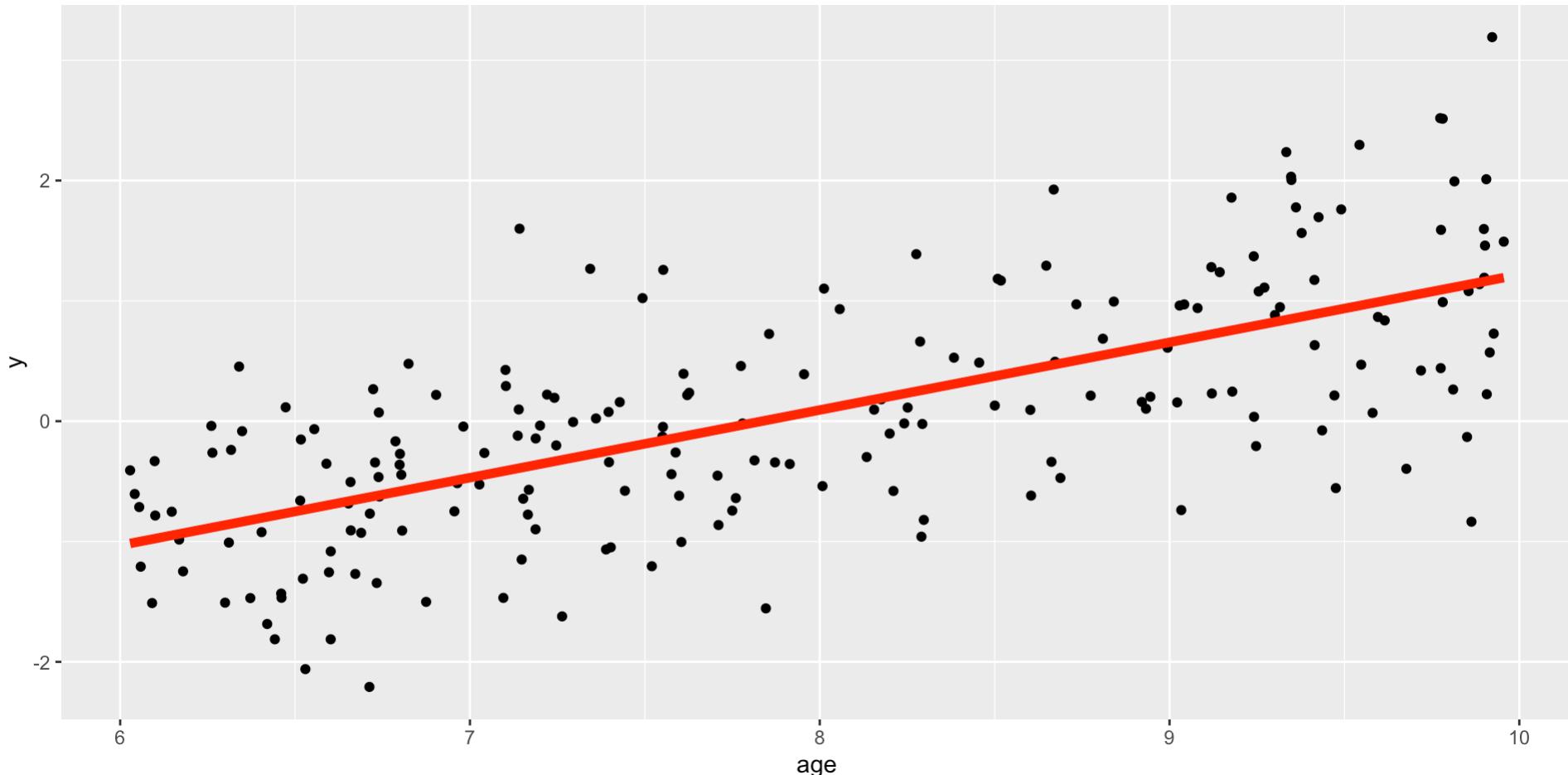
dependent variable: ([variable](#))



# Linear model

using the classical linear predictor

```
1 fit = lm(y~age, data=d)
```



# Linear model

what we dont see it bc its a default parameter but its actually hidden in our code:

- Code

the model uses family gaussian and the identity link function

**link function** in GLMs transforms (re-map) the linear predictor<sup>1</sup>

to the appropriate range of the response variable Y

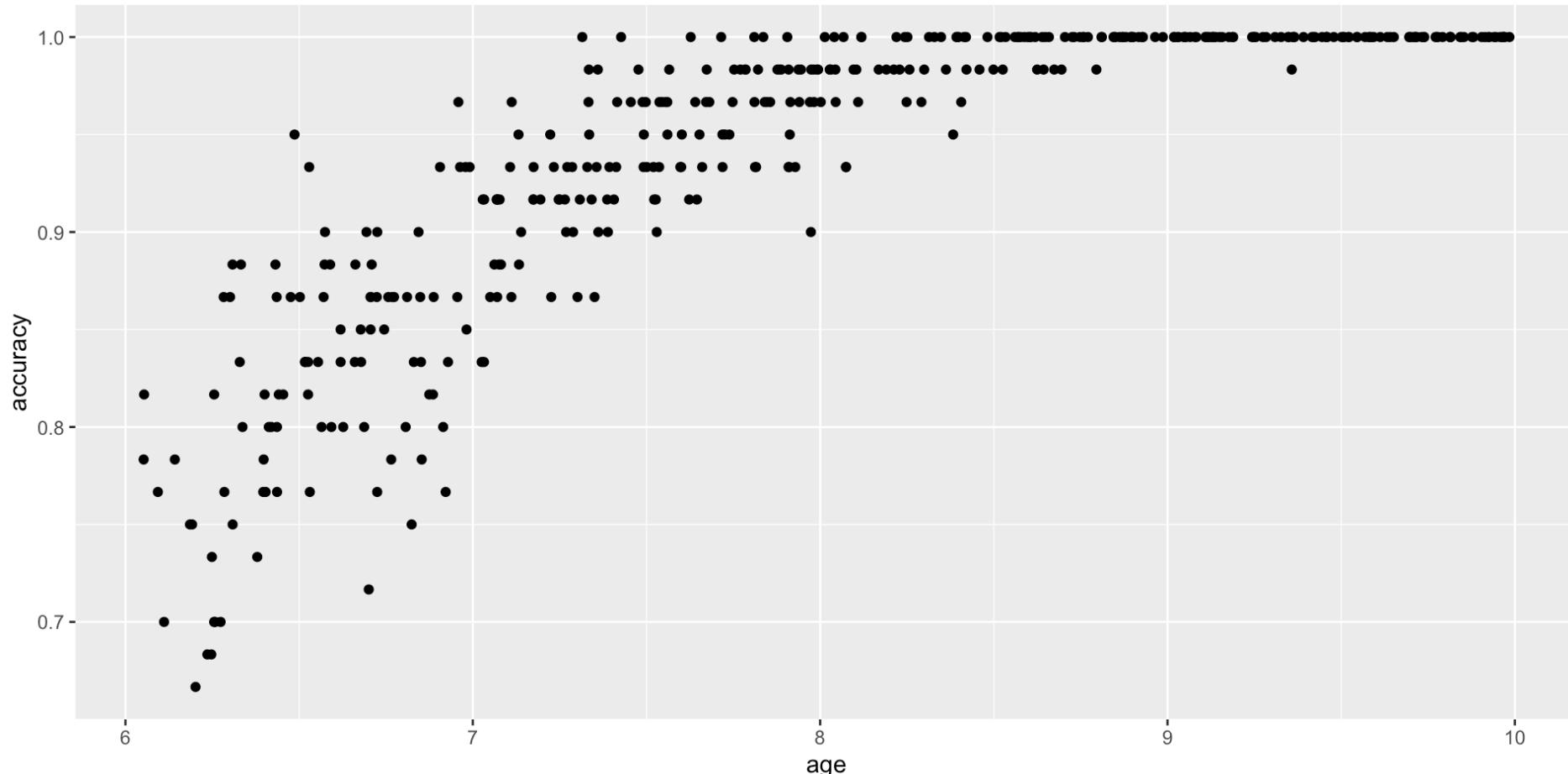
1. often called  $\eta$  - in our example:  $\eta = \beta_0 + \beta_1 \cdot age$

# 2 Example

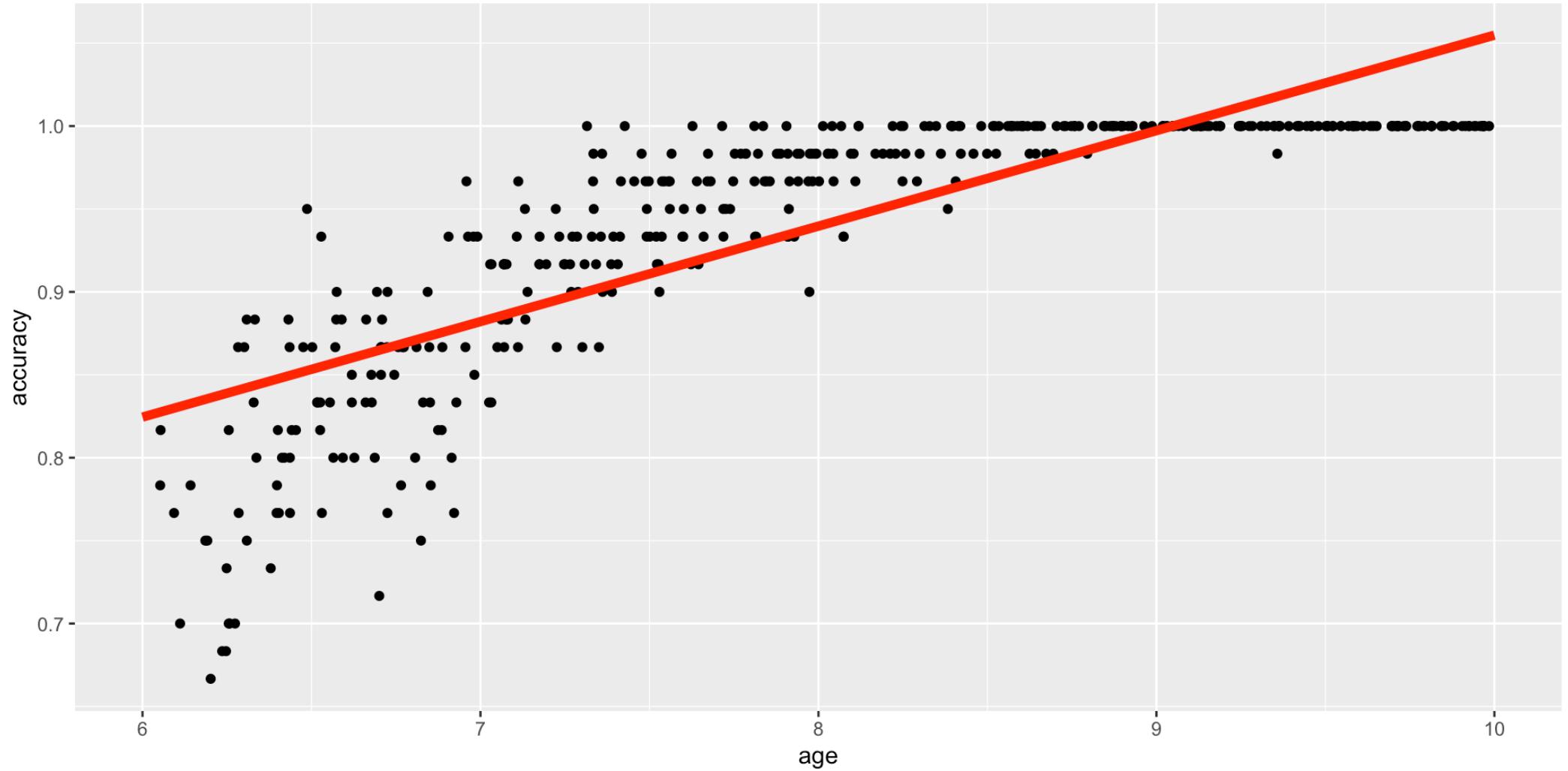
# Simulated dataset 2

independent variable: age in years ([years](#))

dependent variable: mistakes in a TRUE/ FALSE task ([accuracy](#))



# Linear model



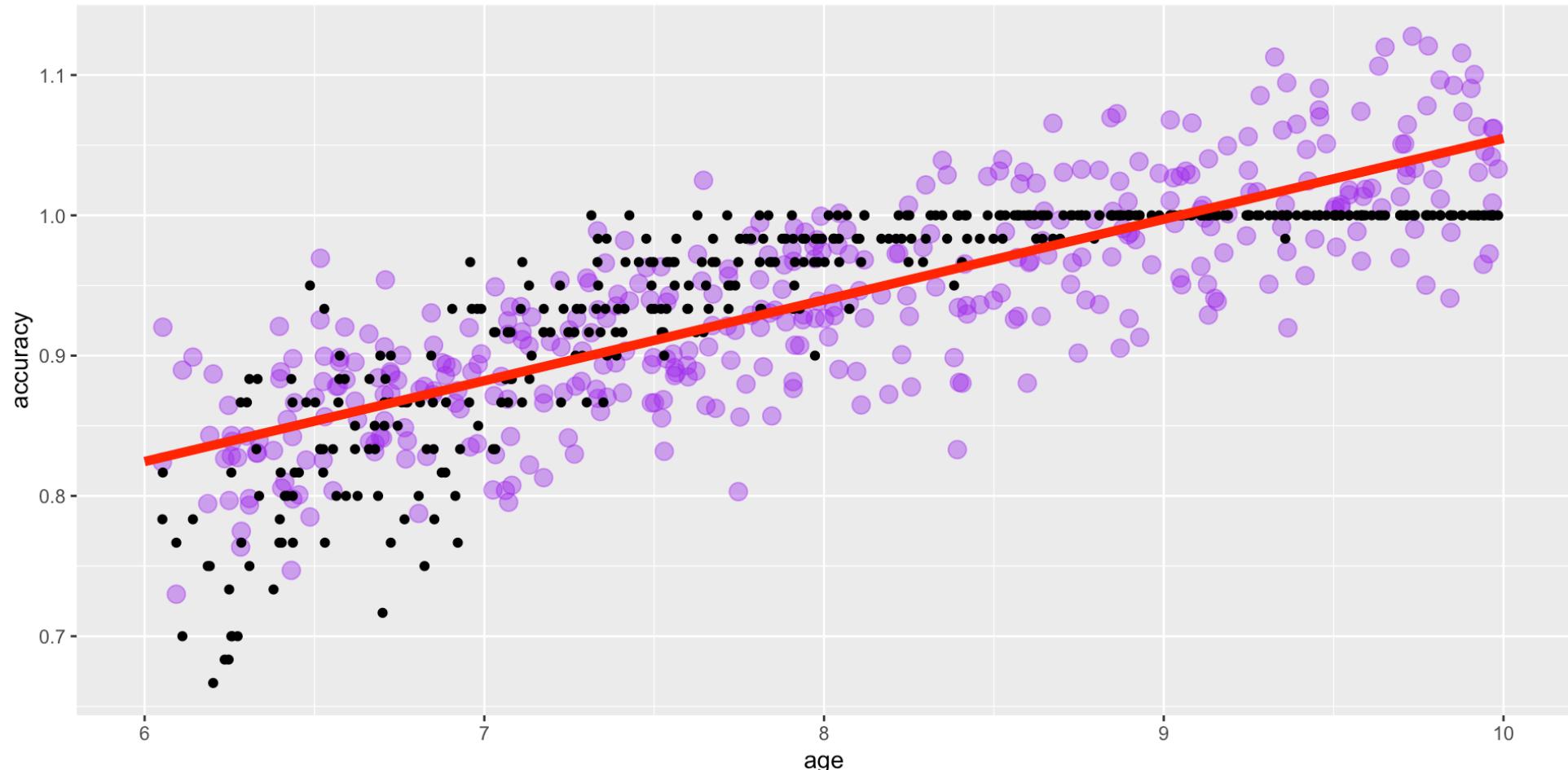
# Linear model

using the classical linear predictor

```
1 fit = lm(accuracy~age, data=d)
```

# Linear model

i nuovi dati simulati dal modello vanno chiaramente fuori dal range [0,1] di possibili valori per l'accuratezza



## Inappropriate model

IN THE FIRST EXAMPLE an identity link was appropriate bc

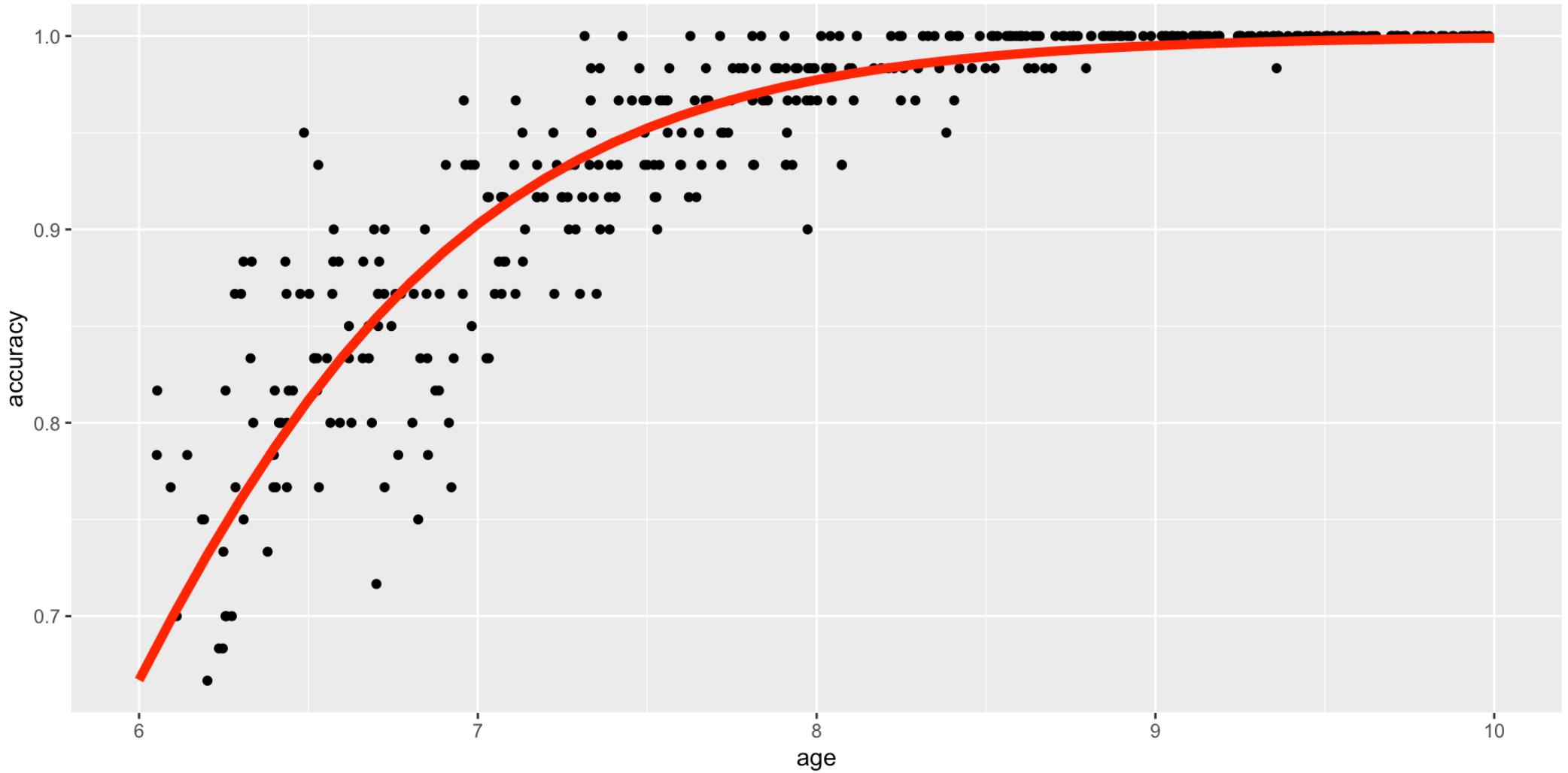
- $y$  (**boh**) spans from  $-\infty$  to  $+\infty$

here an identity link is NOT appropriate bc

- $y$  (**accuracy**) spans from 0 to 1

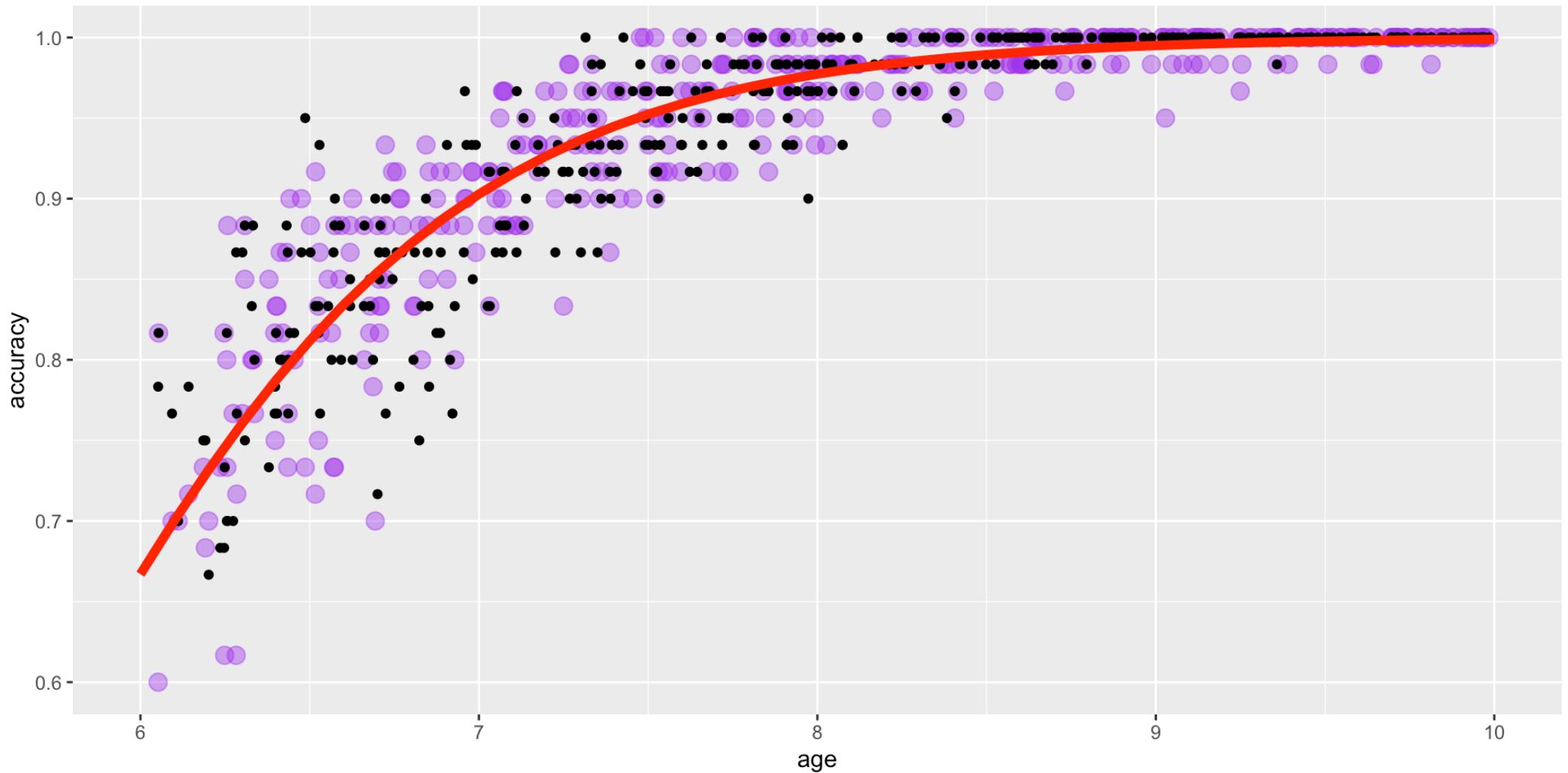


# More appropriate model





# More appropriate model





## More appropriate model

```
1 fit = glm(accuracy ~ age, data=d, family=binomial(link="logit"), weig
```

in this case, `link="logit"` makes sure that `y` spans from 0 and 1

# 3 Studying interactions

## Simulated dataset 2

independent variable: age in years (**years**)

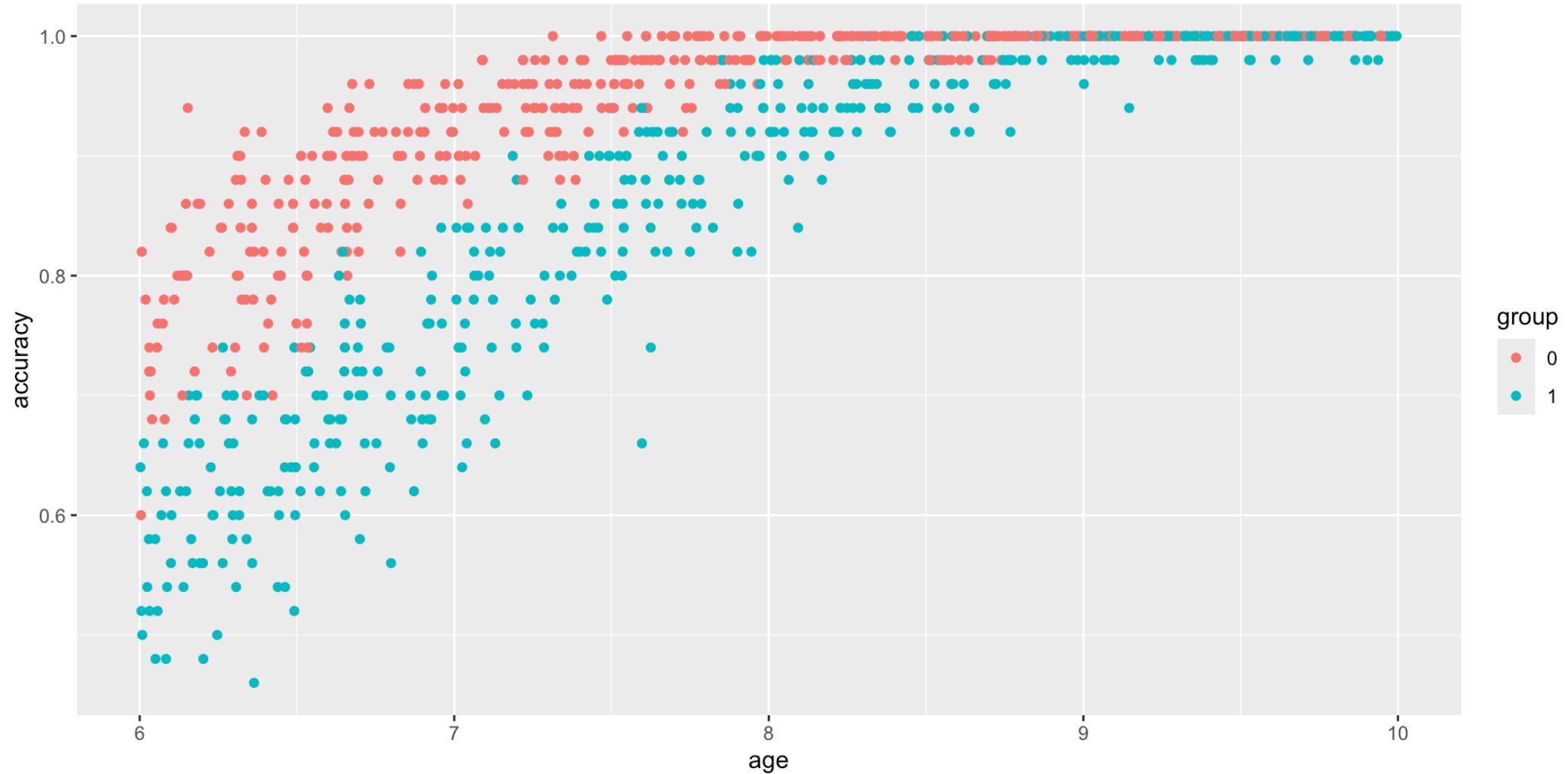
dependent variable: mistakes in a TRUE/FALSE task (**accuracy**)

**adding a new main effect: groups**

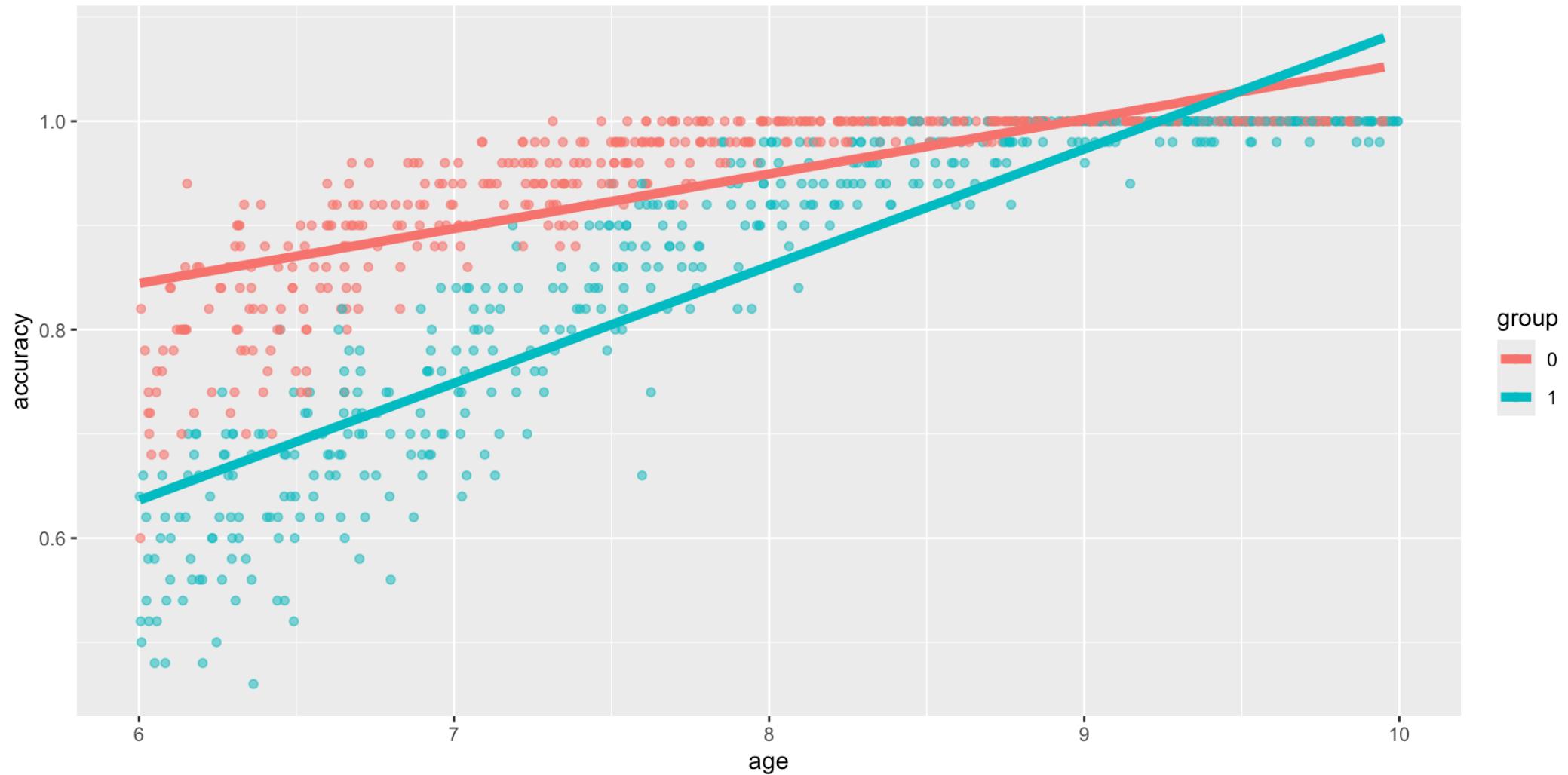
normal kids (**group = 0**)

kids with dyslexia (**group = 1**)

# Simulated dataset 2



# Identity link function



# Identity link function

a **positive** interaction emerges

```
1 fit = glm(accuracy ~ age*group, data=d)
2 summary(fit)
```

Call:

```
glm(formula = accuracy ~ age * group, data = d)
```

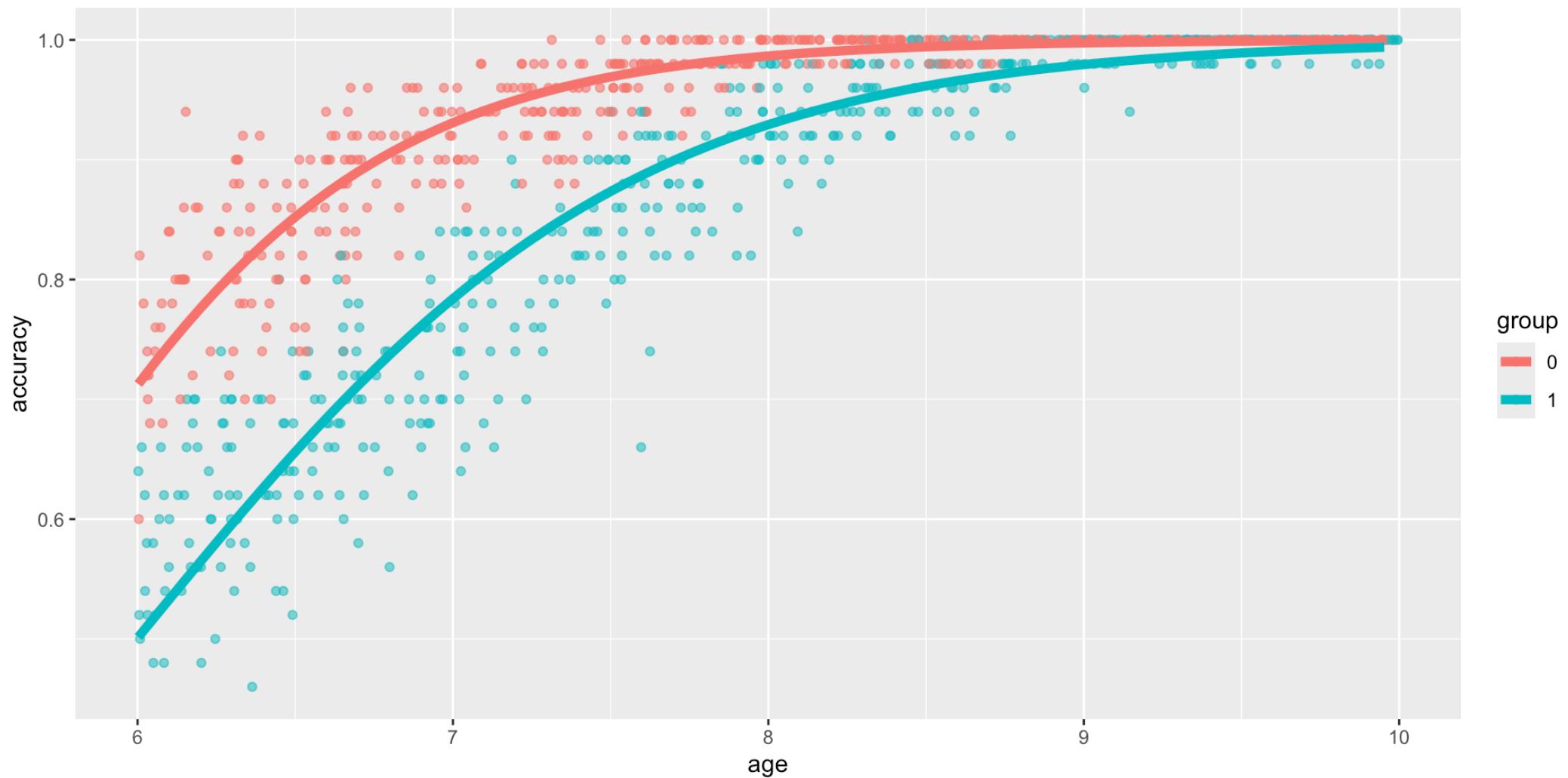
Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	0.529062	0.016916	31.28	<2e-16	***
age	0.052541	0.002103	24.99	<2e-16	***
group1	-0.566758	0.023871	-23.74	<2e-16	***
age:group1	0.059790	0.002967	20.15	<2e-16	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

# Logit link function



# Logit link function

a **negative** interaction emerges

```
1 fit = glm(accuracy ~ age*group, data=d, family=binomial(link="logit"))
2 summary(fit)
```

Call:

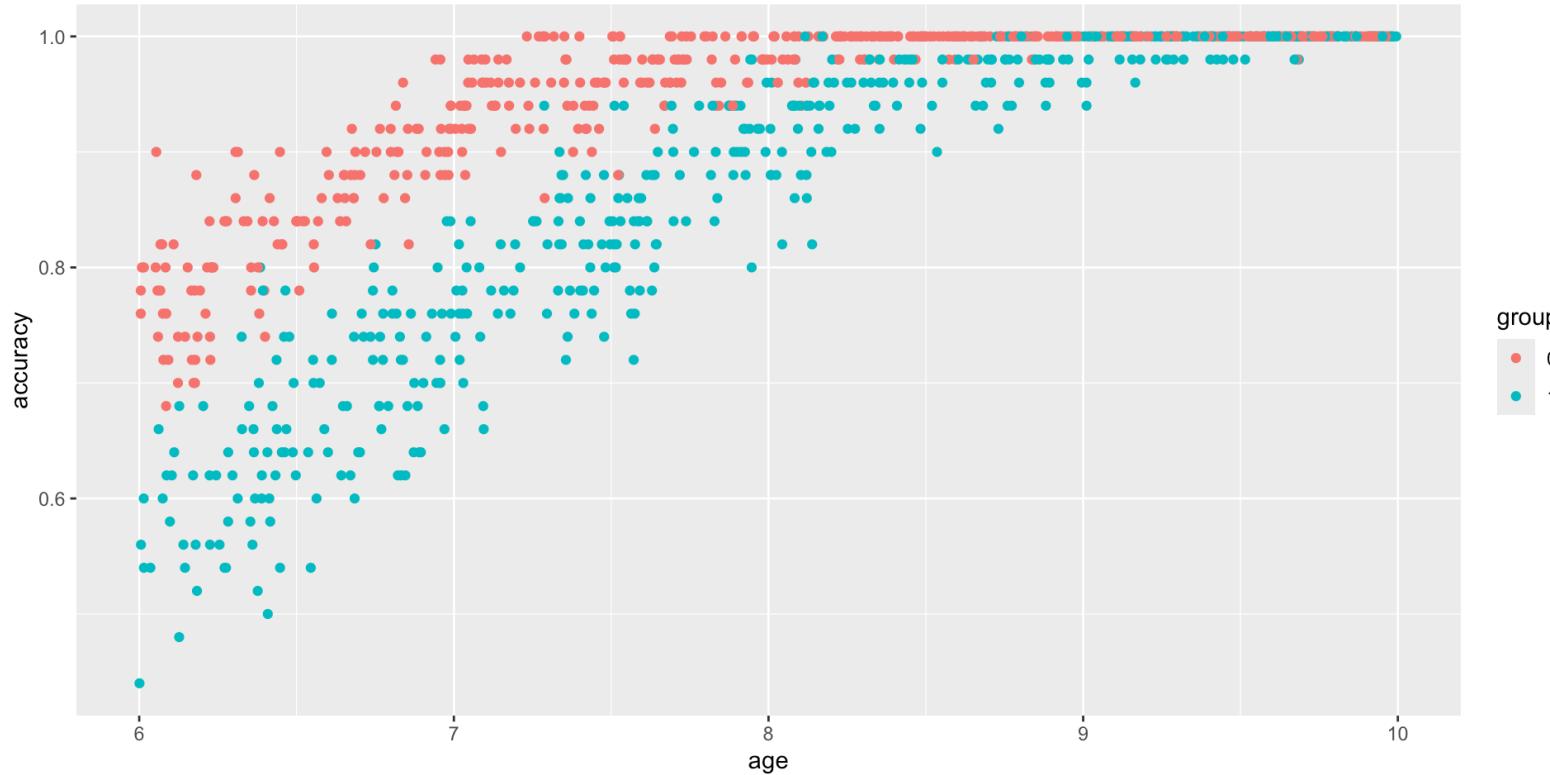
```
glm(formula = accuracy ~ age * group, family = binomial(link = "logit"),
  data = d, weights = rep(k, nrow(d)))
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-9.26482	0.32430	-28.568	< 2e-16	***
age	1.69491	0.04842	35.006	< 2e-16	***
group1	1.55052	0.36909	4.201	2.66e-05	***
age:group1	-0.40870	0.05457	-7.490	6.90e-14	***
---					
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					

# cosa ho effettivamente simulato

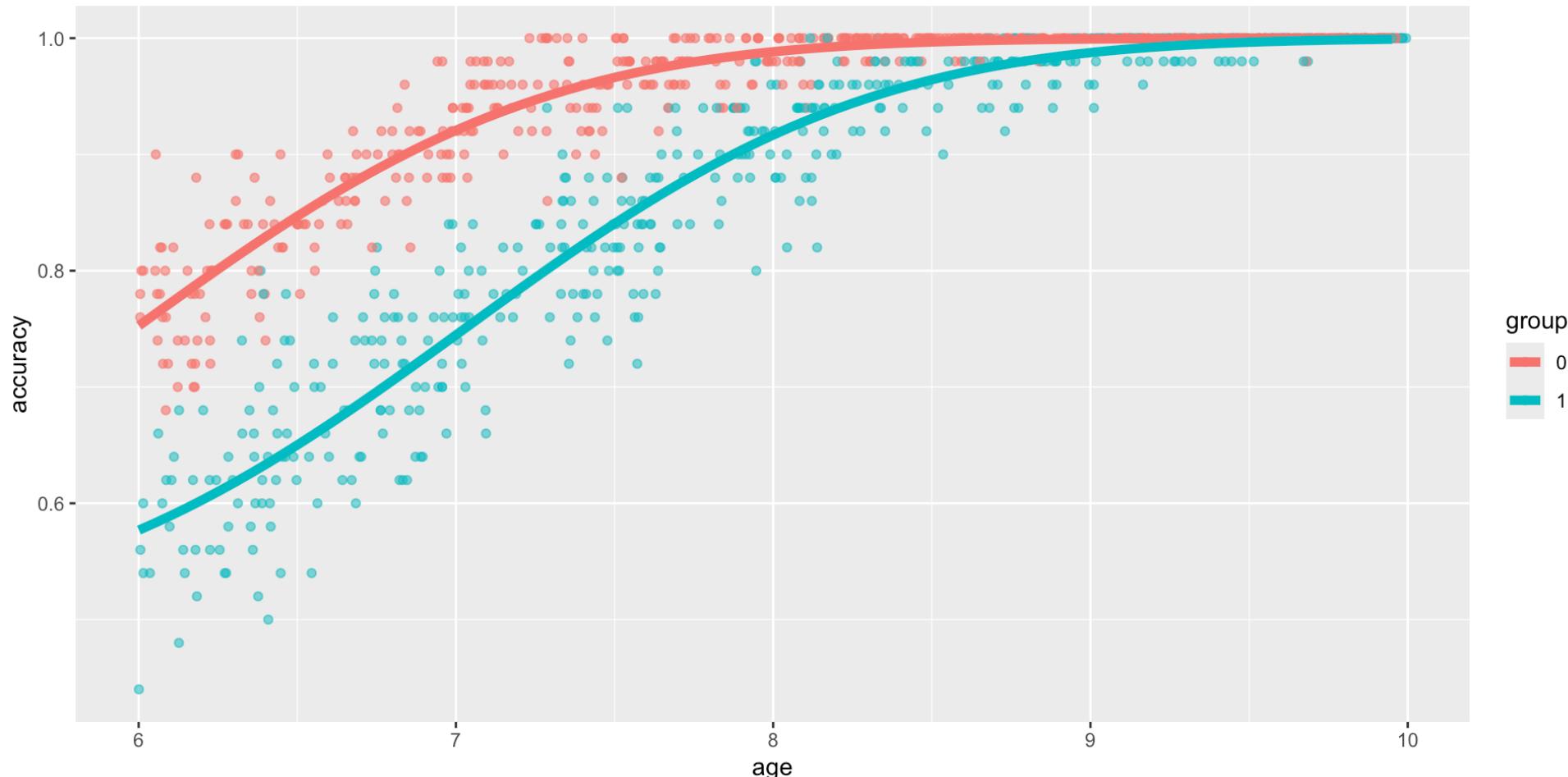
## ► Code



non ho simulato un'interazione, quindi ENTRAMBI i modelli trovano un'interazione che non c'è.

# il vero modello in grado di fissare i dati

let's try out the **multiple alternative forced choice** (50% - bc of the true/false) probit link



# il vero modello in grado di fissare i dati: link="maf.c.probit"

no interaction emerges !!!! as it should

```
1 fit = glm(accuracy ~ age*group, data=d, family=binomial(link=maf.c.pro  
2 summary(fit)
```

Call:

```
glm(formula = accuracy ~ age * group, family = binomial(link =  
maf.c.probit(.m = 2)),  
data = d, weights = rep(k, nrow(d)))
```

Coefficients:

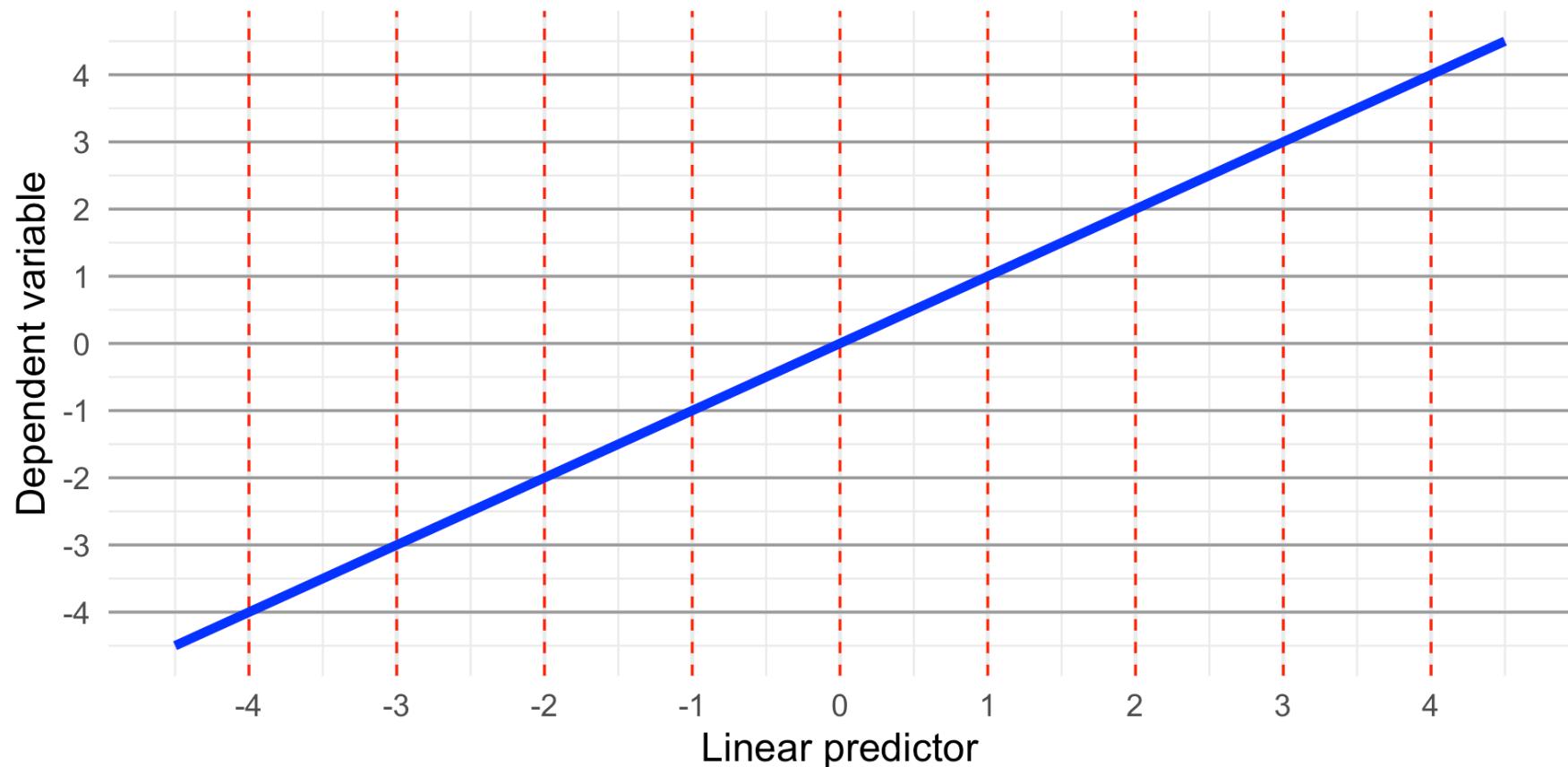
	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-5.911744	0.209295	-28.246	< 2e-16	***
age	0.987424	0.029927	32.994	< 2e-16	***
group1	-1.074050	0.266644	-4.028	5.62e-05	***
age:group1	0.006767	0.036919	0.183	0.855	
---					

# 4 Why interactions

## [link="identity"](#)

equal intervals on X correspond to equal intervals on Y

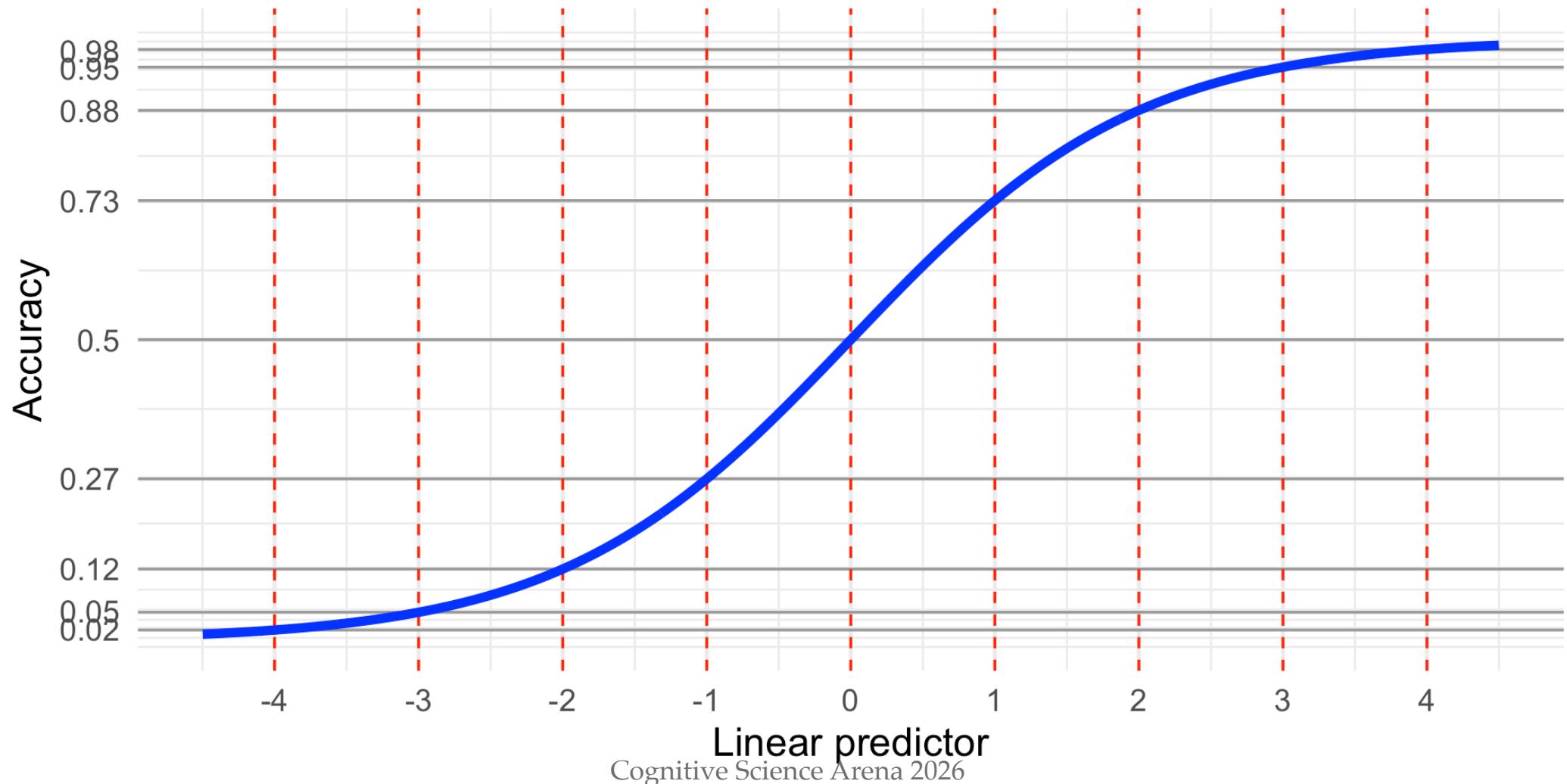
**su y metti i nomi delle variabili dell'esempio**



Linear predictor from our example:  $\eta = \beta_0 + \beta_1 \cdot age$

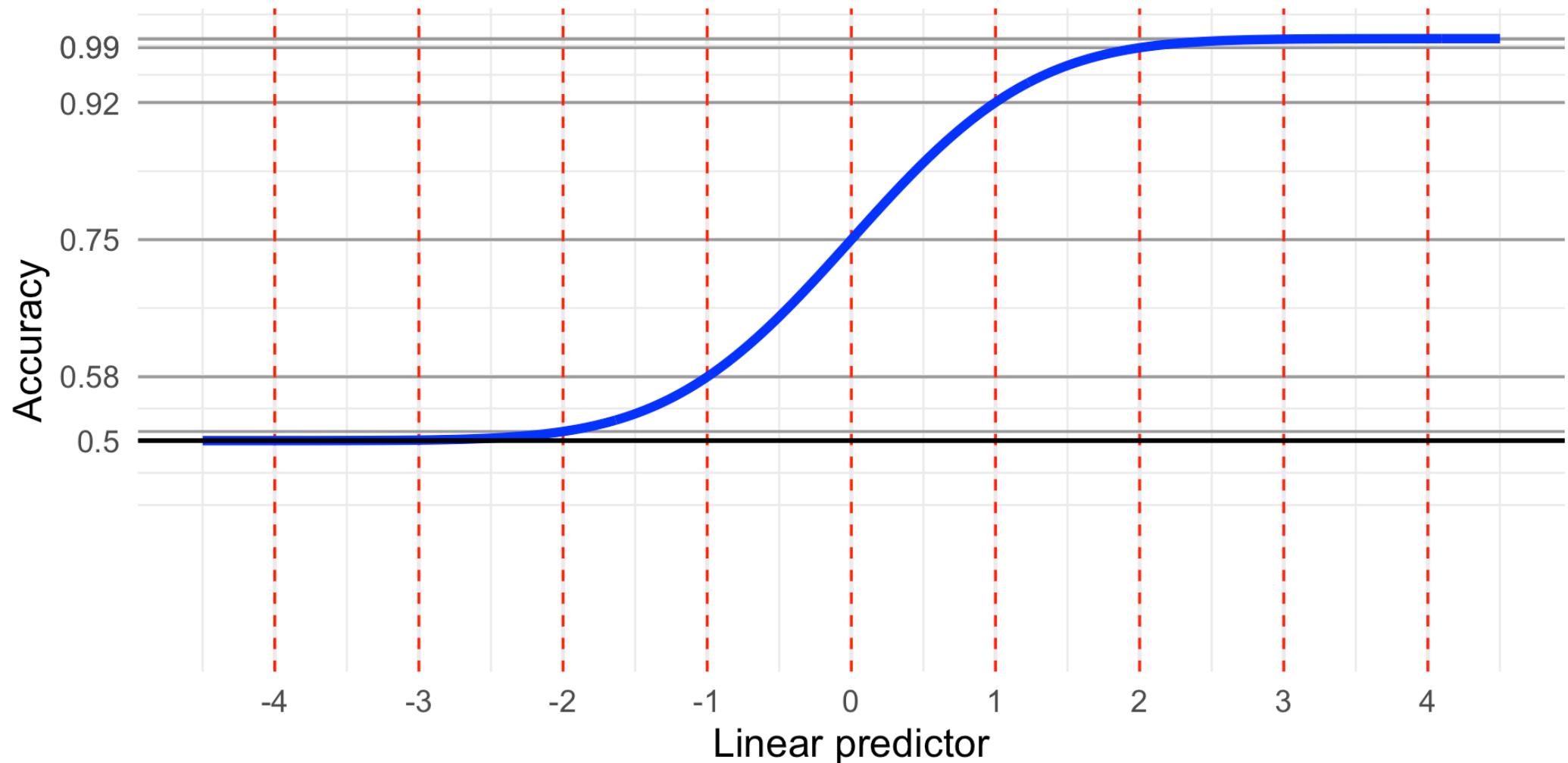
## [link="logit"](#)

equal intervals on X correspond to equal ratios (NOT equal intervals) on Y



`link=mafC.probit(2)`

equal intervals on X do NOT correspond to equal intervals on Y



# Conclusions

Building a model means that we want to find the processo generativo dei dati which, diversamente dal mondo delle simulazioni, we could never know for sure  
to do that we must make important decisions



Tip

choosing the more appropriate **family of distributions** to make sure that the new values of the vd im predicting lie within the bounds



Tip

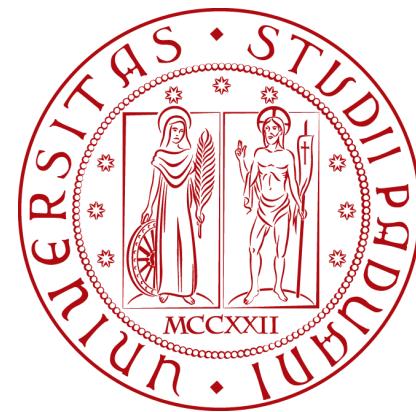
choosing the more appropriate **link function**: otherwise it's very likely you end up finding non linear effects (ie interactions) that are not there!

We're conducting a **systematic review** concerning how often the wrong link functions are used in psychological research + they lead to finding a significant interaction  
so far, quite often

# Materials & Contact

Data simulation, code and presentation are available on GitHub at  
[sitalaura/link-functions](https://github.com/sitalaura/link-functions)

Questions and feedbacks [laura.sita@studenti.unipd.it](mailto:laura.sita@studenti.unipd.it)



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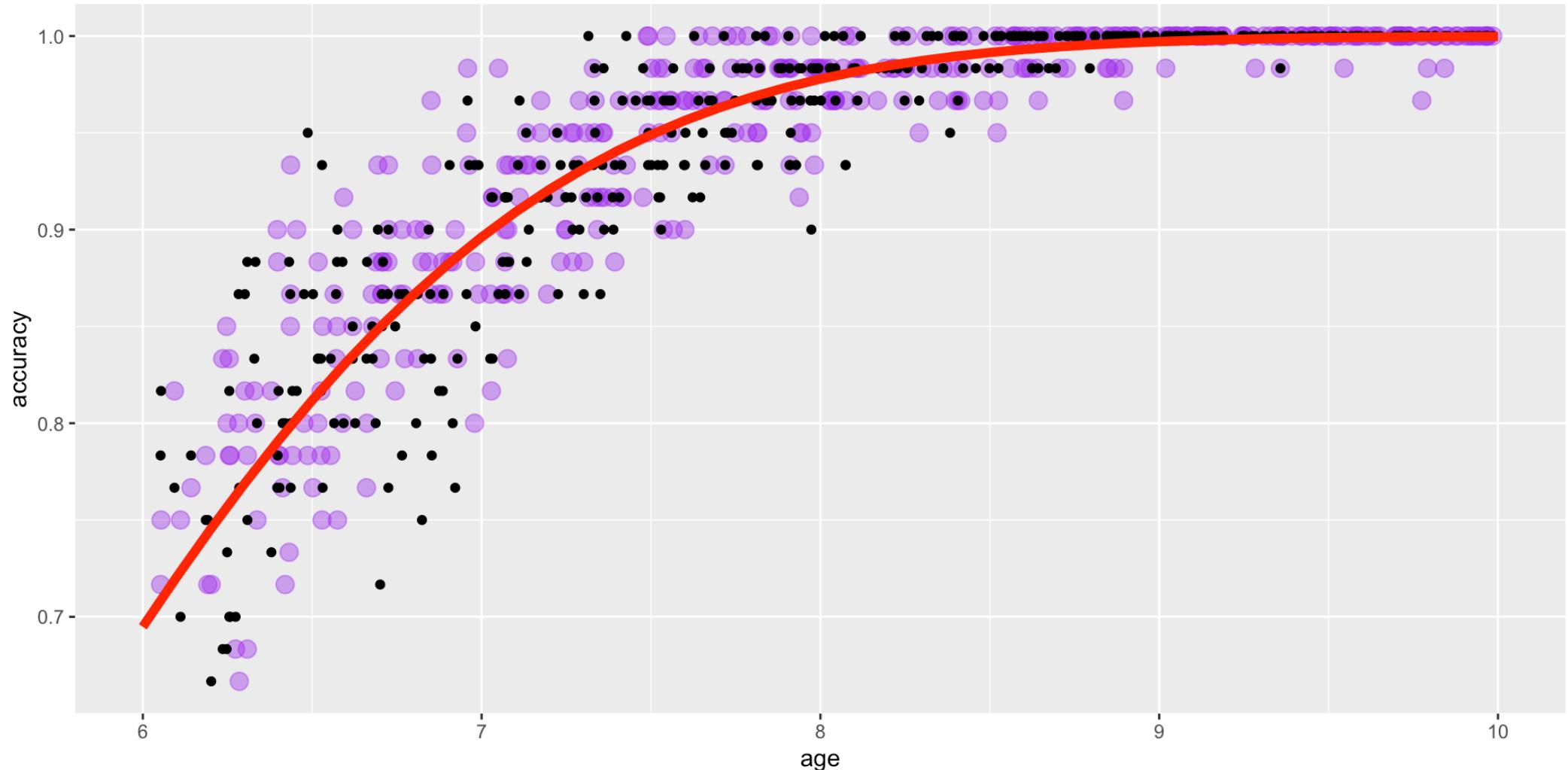
# Thank you

Special thanks to

# Supplementary materials

# Posterior predictive check link="probit"

```
1 fit = glm(accuracy ~ age, data=d, family=binomial(link="probit"), wei
```



# Interaction with link="probit"

a **negative** interaction emerges

```
1 fit = glm(accuracy ~ age*group, data=d, family=binomial(link="probit")
2 summary(fit)
```

Call:

```
glm(formula = accuracy ~ age * group, family = binomial(link =
"probit"),
  data = d, weights = rep(k, nrow(d)))
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	2.21133	0.03018	73.280	< 2e-16	***
age	0.81113	0.02295	35.337	< 2e-16	***
group1	-0.79152	0.03400	-23.279	< 2e-16	***
age:group1	-0.11299	0.02637	-4.285	1.83e-05	***
---					