

# Propensity Score Diagnostics

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# Checking balance

## Love plots (Standardized Mean Difference)

## ECDF plots

# Standardized Mean Difference (SMD)

$$d = \frac{\bar{x}_{treatment} - \bar{x}_{control}}{\sqrt{\frac{s_{treatment}^2 + s_{control}^2}{2}}}$$

# SMD in R

## 1 Calculate standardized mean differences

```
library(tidysmd)
library(tidyverse)

smds <- tidy_smd(
  df,
  .vars = c(confounder_1, confounder_2, ...),
  .group = exposure,
  .wts = wts # weight is optional
)
```

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```



# SMD in R

## 2 Plot them! (in a Love plot!)

```
ggplot(  
  data = smds,  
  aes(x = abs(smd), y = variable, group = weights, color = weights)  
) +  
  geom_line(orientation = "y") +  
  geom_point() +  
  geom_vline(xintercept = 0.1, color = "black", size = 0.1)
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# SMD in R

## 2 Plot them! (in a Love plot!)

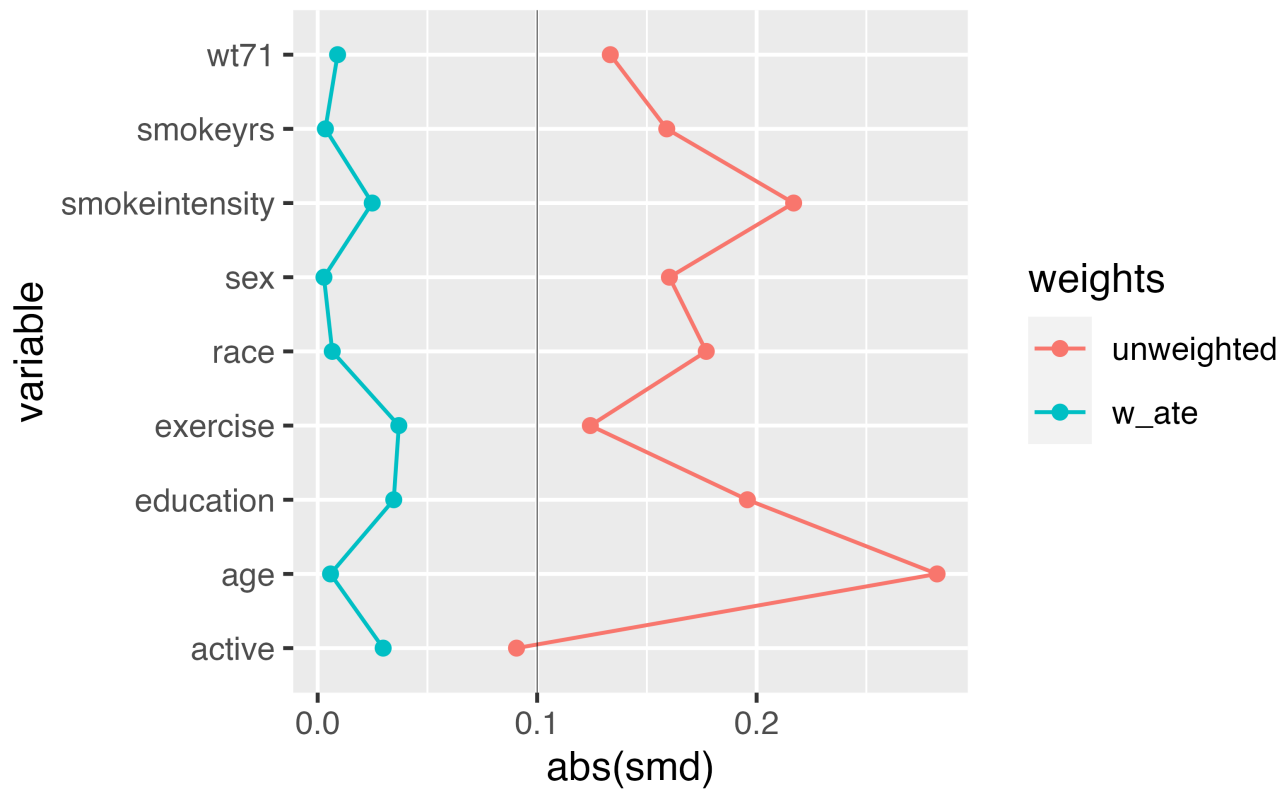
```
ggplot(  
  data = smds,  
  aes(x = abs(smd), y = variable, group = weights, color = weights)  
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  geom_line(orientation = "y") +  
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# Love plot



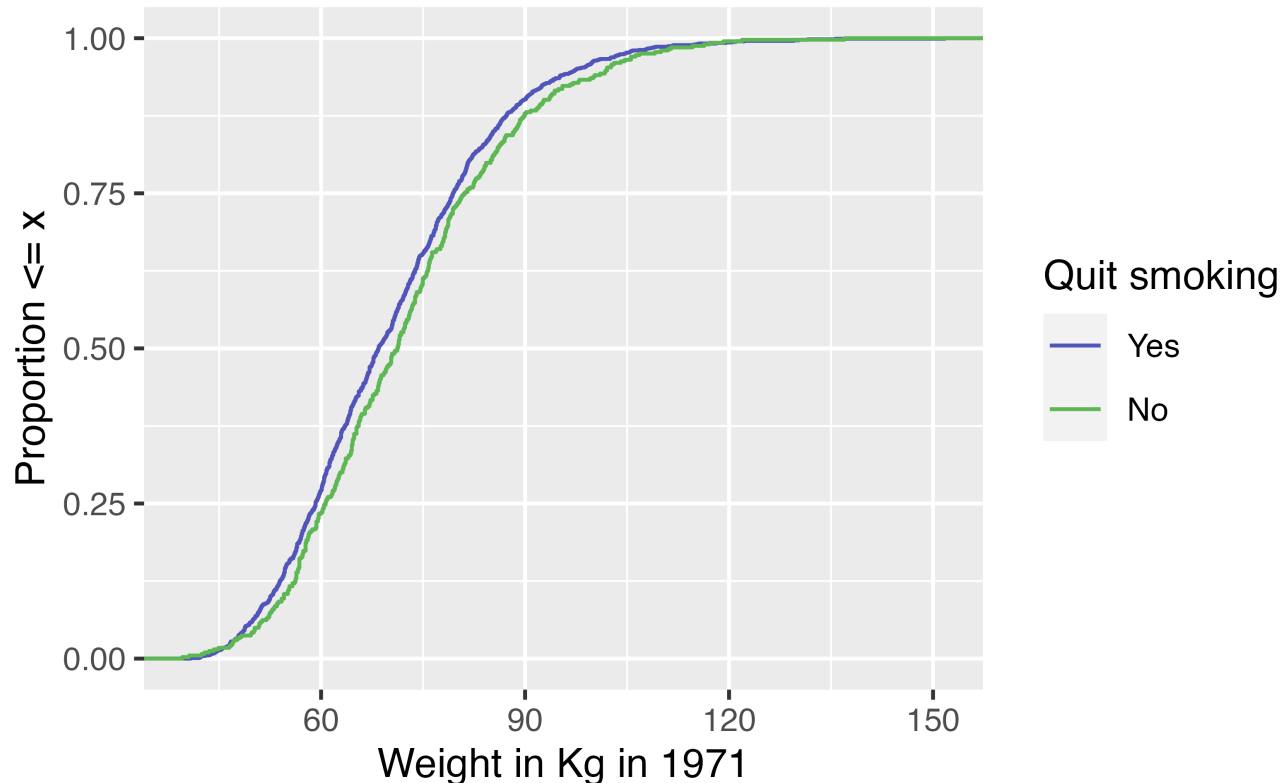
## Your turn 1

- 1 Create a Love Plot for the propensity score weighting you created in the previous exercise**

10:00

# ECDF

For continuous variables, it can be helpful to look at the **whole** distribution pre and post-weighting rather than a single summary measure





# Unweighted ECDF

```
library(ggecdf)
```

```
ggplot(df, aes(x = wt71, color = factor(qsmk))) +  
  geom_ecdf() +  
  scale_color_manual("Quit smoking", values = c("#5154B8", "#5DB854"),  
                    labels = c("Yes", "No")) +  
  xlab("Weight in Kg in 1971") +  
  ylab("Proportion <= x")
```

# Unweighted ECDF

```
library(ggecdf)

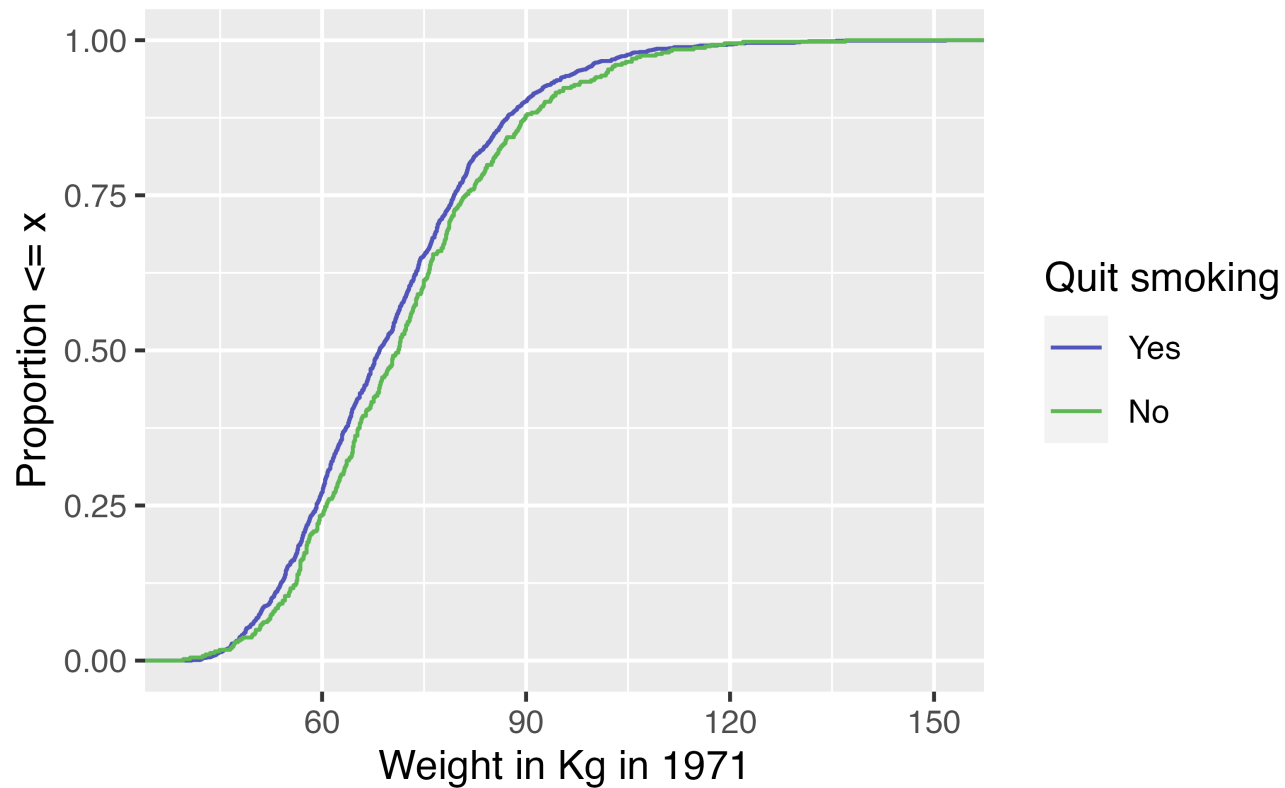
ggplot(df, aes(x = wt71, color = factor(qsmk))) +
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  scale_color_manual("Quit smoking", values = c("#5154B8", "#5DB854"),
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```

# Unweighted ECDF



# Weighted ECDF

```
library(ggecdf)

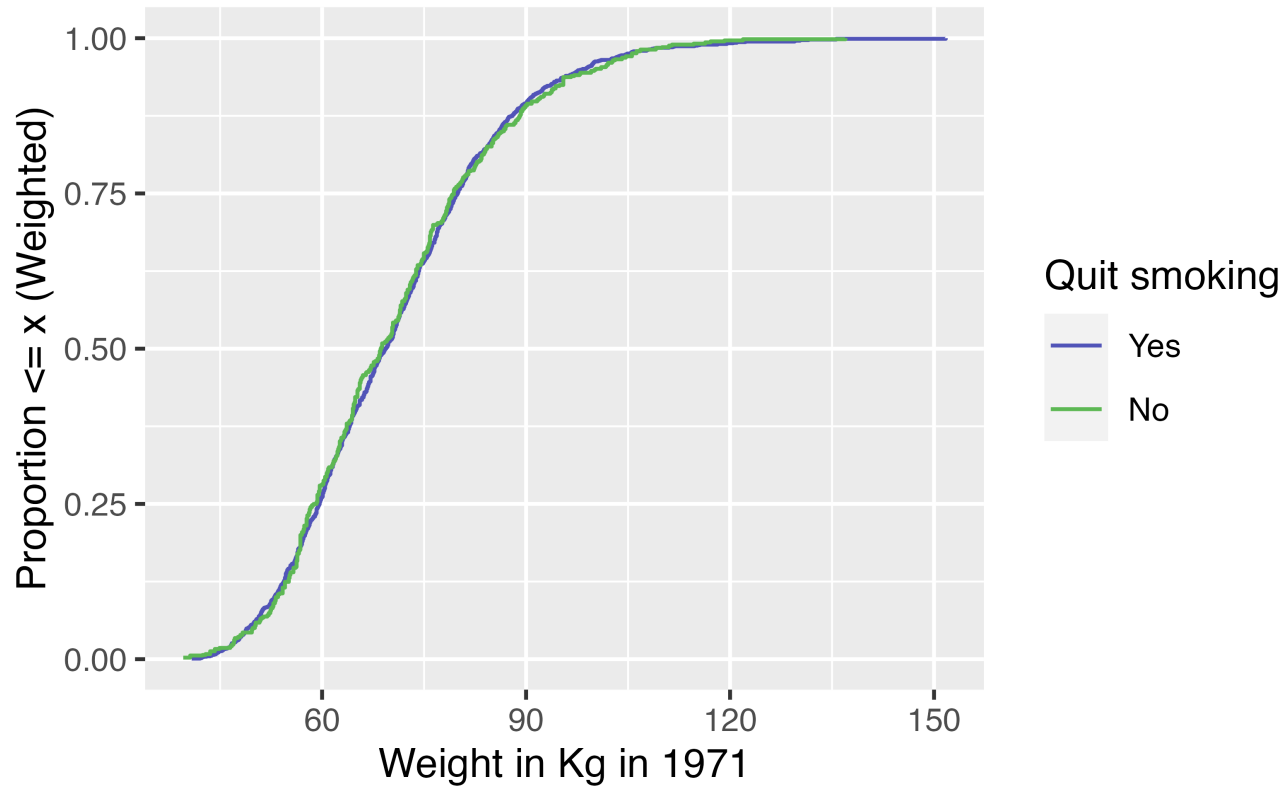
ggplot(df, aes(x = wt71, color = factor(qsmk))) +
  geom_ecdf(aes(weights = w_ate)) +
  scale_color_manual("Quit smoking", values = c("#5154B8", "#5DB854"),
                    labels = c("Yes", "No")) +
  xlab("Weight in Kg in 1971") +
  ylab("Proportion <= x (Weighted)")
```

# Weighted ECDF

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                    labels = c("Yes", "No")) +
  xlab("Weight in Kg in 1971") +
  ylab("Proportion <= x (Weighted)")
```

# Weighted ECDF



## Your turn 2

- 1 Create an unweighted ECDF examining the weather\_wdwhigh confounder by whether or not the day had Extra Magic Hours.**
- 2 Create a weighted ECDF examining the weather\_wdwhigh confounder**

10:00



## **Bonus!** Weighted Tables in R

# Weighted Tables in R

## 1 Create a "design object" to incorporate the weights

```
library(survey)

svy_des <- svydesign(
  ids = ~ 1,
  data = df,
  weights = ~ wts
)
```

# Weighted Tables in R

## 2 Pass to gtsummary::tbl\_svysummary()

```
library(gtsummary)
tbl_svysummary(svy_des, by = x) %>%
  add_difference(everything() ~ "smd")
# modify_column_hide(ci) to hide CI column
```

Characteristic	0, N = 1,565 <sup>1</sup>	1, N = 1,561 <sup>1</sup>	Difference <sup>2</sup>
WEIGHT IN KILOGRAMS IN 1971	69 (60, 80)	69 (59, 79)	0.01
0: WHITE 1: BLACK OR OTHER IN 1971			0.01
0	1,359 (87%)	1,352 (87%)	
1	206 (13%)	209 (13%)	
AGE IN 1971	43 (33, 52)	43 (33, 53)	-0.01
0: MALE 1: FEMALE			0.00
0	764 (49%)	764 (49%)	
1	802 (51%)	797 (51%)	
NUMBER OF CIGARETTES SMOKED PER DAY IN 1971	20 (10, 25)	20 (10, 30)	0.02
YEARS OF SMOKING	24 (15, 33)	24 (14, 33)	0.00
IN RECREATION, HOW MUCH EXERCISE? IN 1971, 0:much exercise,1:moderate exercise,2:little or no exercise			0.04
0	302 (19%)	294 (19%)	
1	665 (42%)	691 (44%)	
2	599 (38%)	576 (37%)	
IN YOUR USUAL DAY, HOW ACTIVE ARE YOU? IN 1971, 0:very active, 1:moderately active, 2:inactive			0.03
0	700 (45%)	684 (44%)	
1	718 (46%)	738 (47%)	
2	147 (9.4%)	138 (8.9%)	
<sup>1</sup> Median (IQR); n (%)			
<sup>2</sup> Standardized Mean Difference			