Fitting the outcome model

Lucy D'Agostino McGowan

Wake Forest University

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Outcome Model

```
library(broom)

lm(outcome ~ exposure, data = df, weights = wts) %>%
  tidy()
```

- **▼** This will get us the point estimate
- X This will get NOT us the correct confidence intervals
- {rsample}

```
fit_ipw <- function(split, ...) {</pre>
  .df <- analysis(split)</pre>
  # fit propensity score model
  propensity model <- glm(</pre>
    exposure ~ confounder_1 + confounder_2 + ...
    family = binomial(),
    data = .df
  # calculate inverse probability weights
  .df <- propensity_model %>%
    augment(type.predict = "response", data = .df) %>%
    mutate(wts = 1 / ifelse(exposure == 0, 1 - .fitted, .fitted))
  # fit correctly bootsrapped ipw model
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Use {rsample} to bootstrap our causal effect

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library(rsample)
# fit ipw model to bootstrapped samples
ipw_results <- bootstraps(df, 1000, apparent = TRUE) %>%
  mutate(results = map(splits, fit_ipw))
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3 Pull out the causal effect

```
# get t-statistic-based CIs
boot_estimate <- int_t(ipw_results, results) %>%
  filter(term == "exposure")
```

Your Turn

1 Create a function called ipw_fit that fits the propensity score model and the weighted outcome model for the effect between extra_magic_morning and avg_spostmin

2 Using the bootstraps() and int_t() functions to estimate the final 2:00