

Causal Diagrams in R

Malcolm Barrett

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**Draw your causal
assumptions with causal
directed acyclic graphs
(DAGs)**

The basic idea

- 1 Specify your causal question
- 2 Use domain knowledge
- 3 Write variables as nodes
- 4 Write causal pathways as arrows
(edges)

ggdag

dagitty

ggplot2
gggraph

dagitty

ggplot2
gggraph

powerful,
robust
algorithms

dagitty

powerful,
robust
algorithms

ggplot2
ggraph

unlimited
flexibility

beautiful
plots

dagitty

ggplot2
ggraph

Data
structure:
tidy DAGs

```
graph TD; A[Data structure: tidy DAGs] --> B[dagitty]; A --> C[ggplot2]; A --> D[ggraph];
```

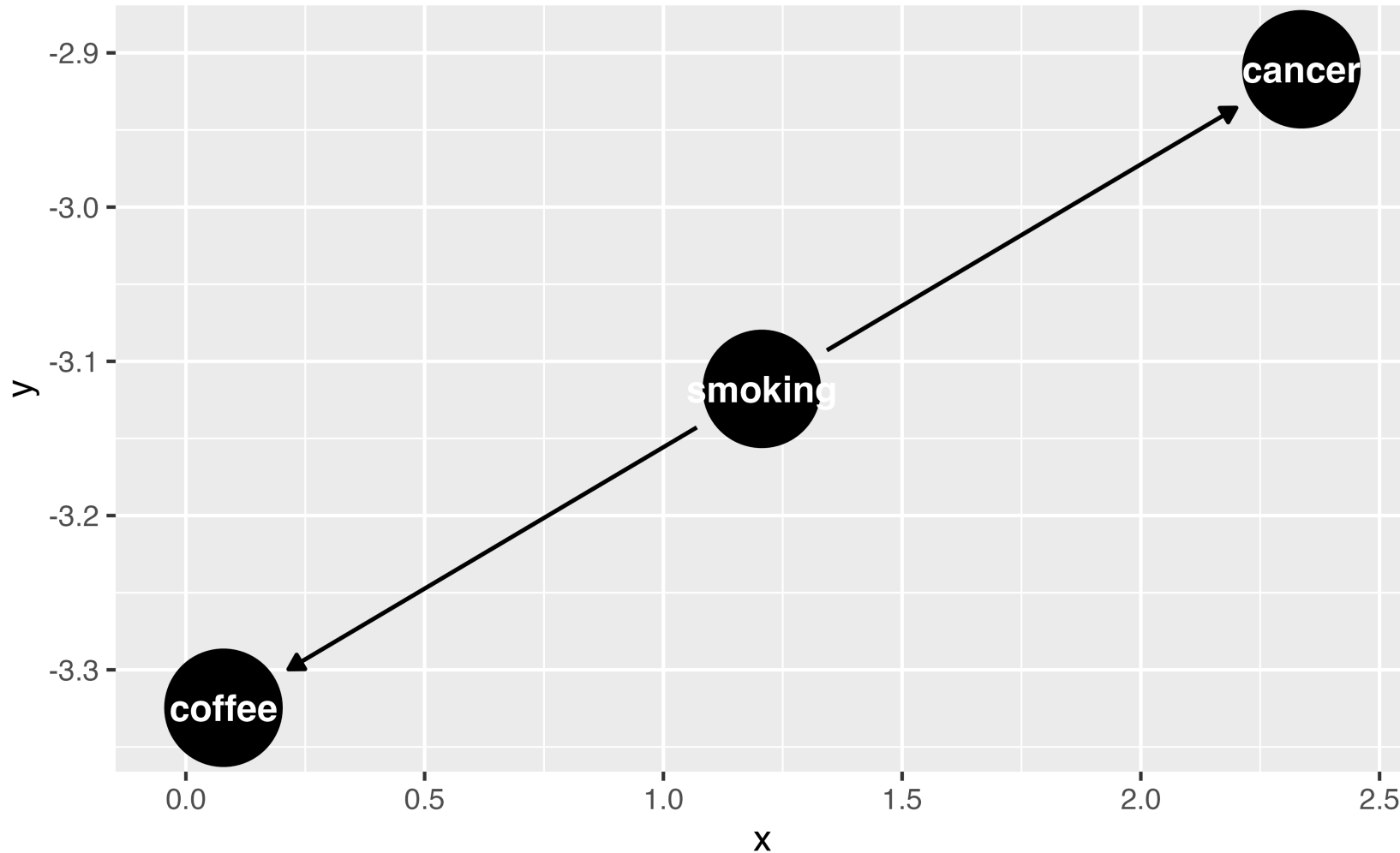

Step 1: Specify your DAG

```
1 dagify(  
2     cancer ~ smoking,  
3     coffee ~ smoking  
4 )
```

Step 1: Specify your DAG

```
1 dagify(  
2   cancer ~ smoking,  
3   coffee ~ smoking  
4 ) |> ggdag()
```

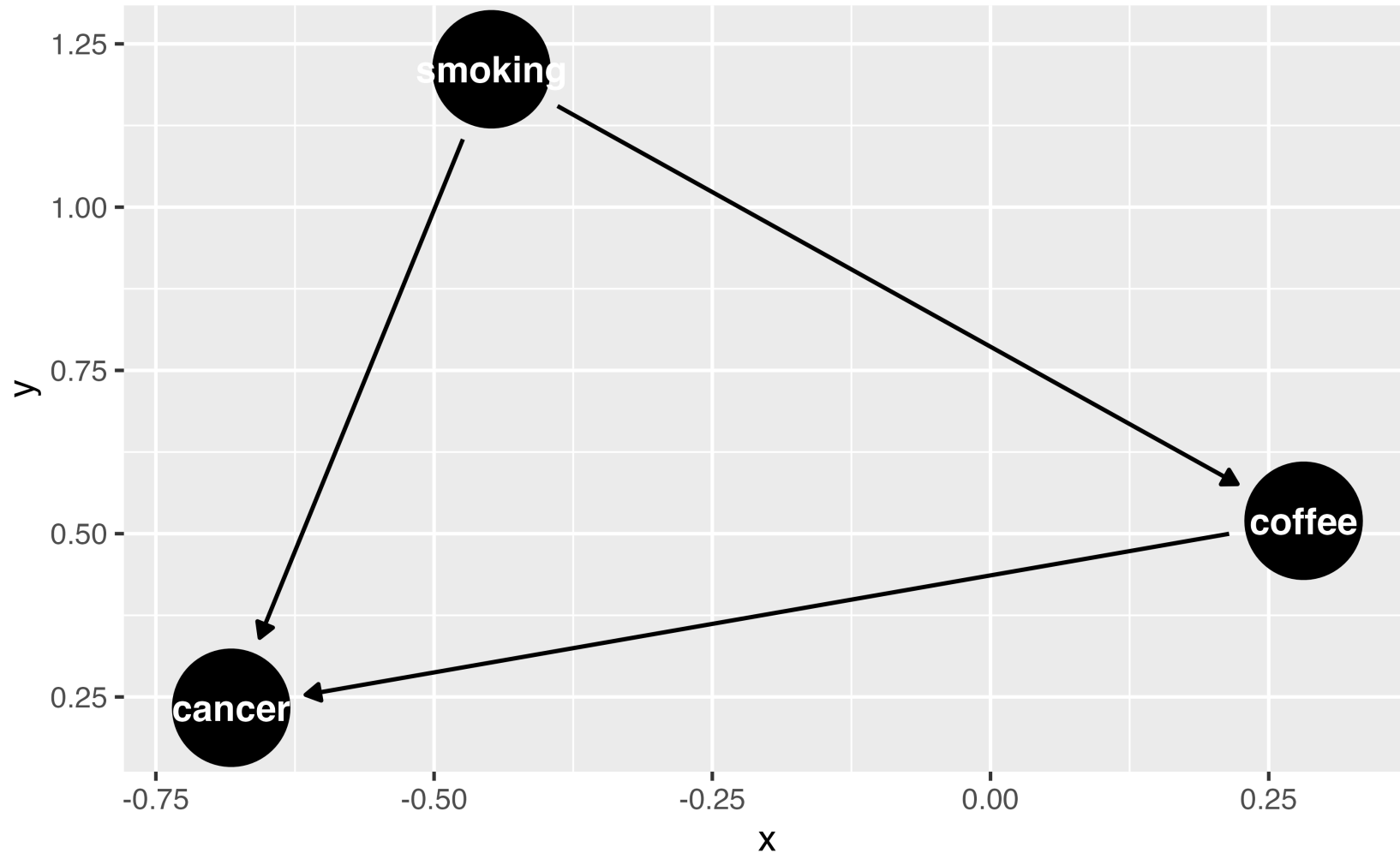
Step 1: Specify your DAG



Step 1: Specify your DAG

```
1 dagify(  
2   cancer ~ smoking + coffee,  
3   coffee ~ smoking  
4 ) |> ggdag()
```

Step 1: Specify your DAG



Your Turn 1 (04-dags-exercises.qmd)

Specify a DAG with `dagify()`. Write your assumption that **smoking** causes **cancer** as a formula.

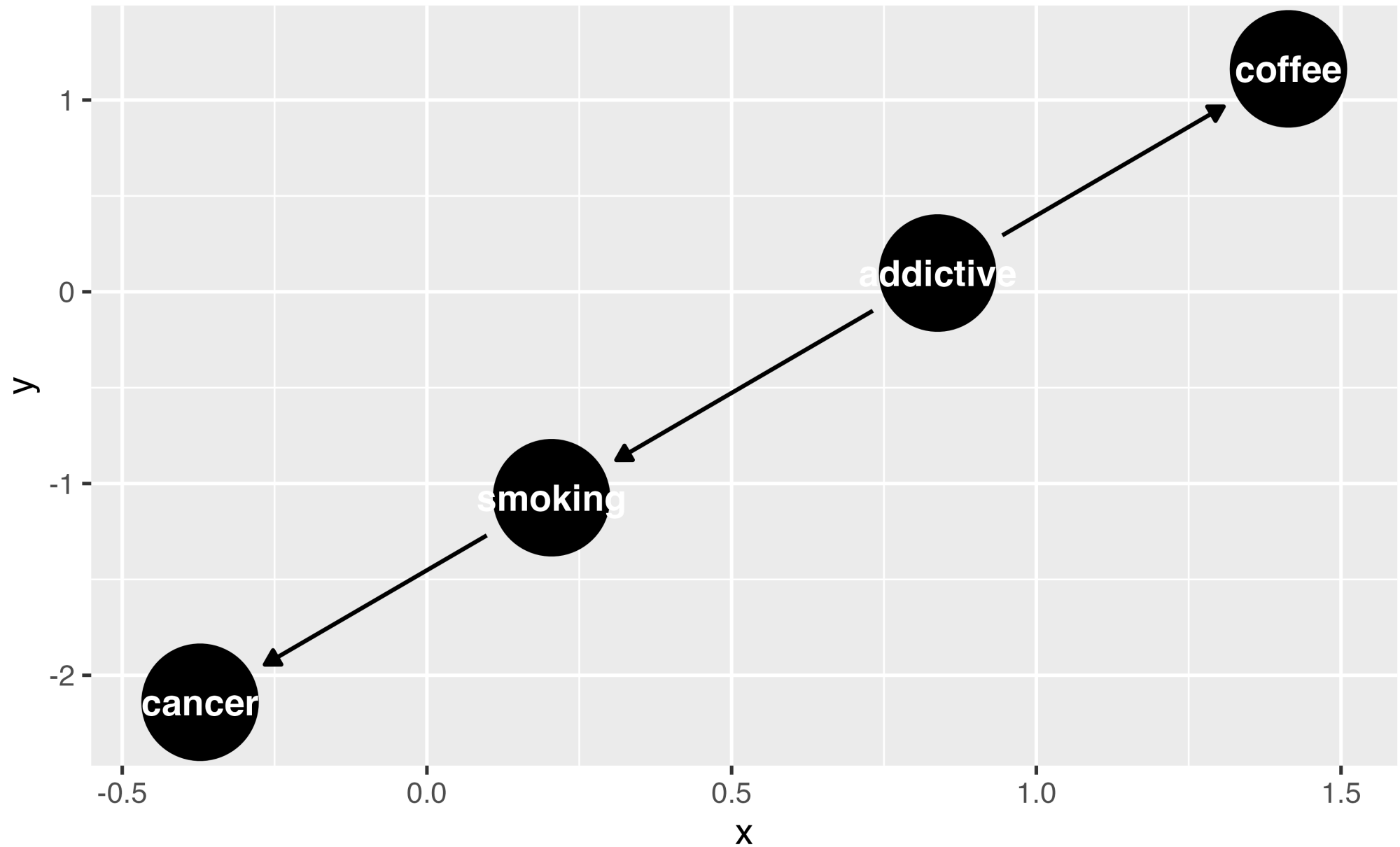
We're going to assume that coffee does not cause cancer, so there's no formula for that. But we still need to declare our causal question. Specify "coffee" as the exposure and "cancer" as the outcome (both in quotations marks).

Plot the DAG using `ggdag()`

Your Turn 1 (02-dags-exercises.qmd)

```
1 coffee_cancer_dag <- dagify(  
2   cancer ~ smoking,  
3   smoking ~ addictive,  
4   coffee ~ addictive,  
5   exposure = "coffee",  
6   outcome = "cancer",  
7   labels = c(  
8     "coffee" = "Coffee",  
9     "cancer" = "Lung Cancer",  
10    "smoking" = "Smoking",  
11    "addictive" = "Addictive \nBehavior"  
12  )  
13 )
```

```
1 ggdag(coffee_cancer_dag)
```



Causal effects and backdoor paths

Ok, correlation \neq causation. But why not?

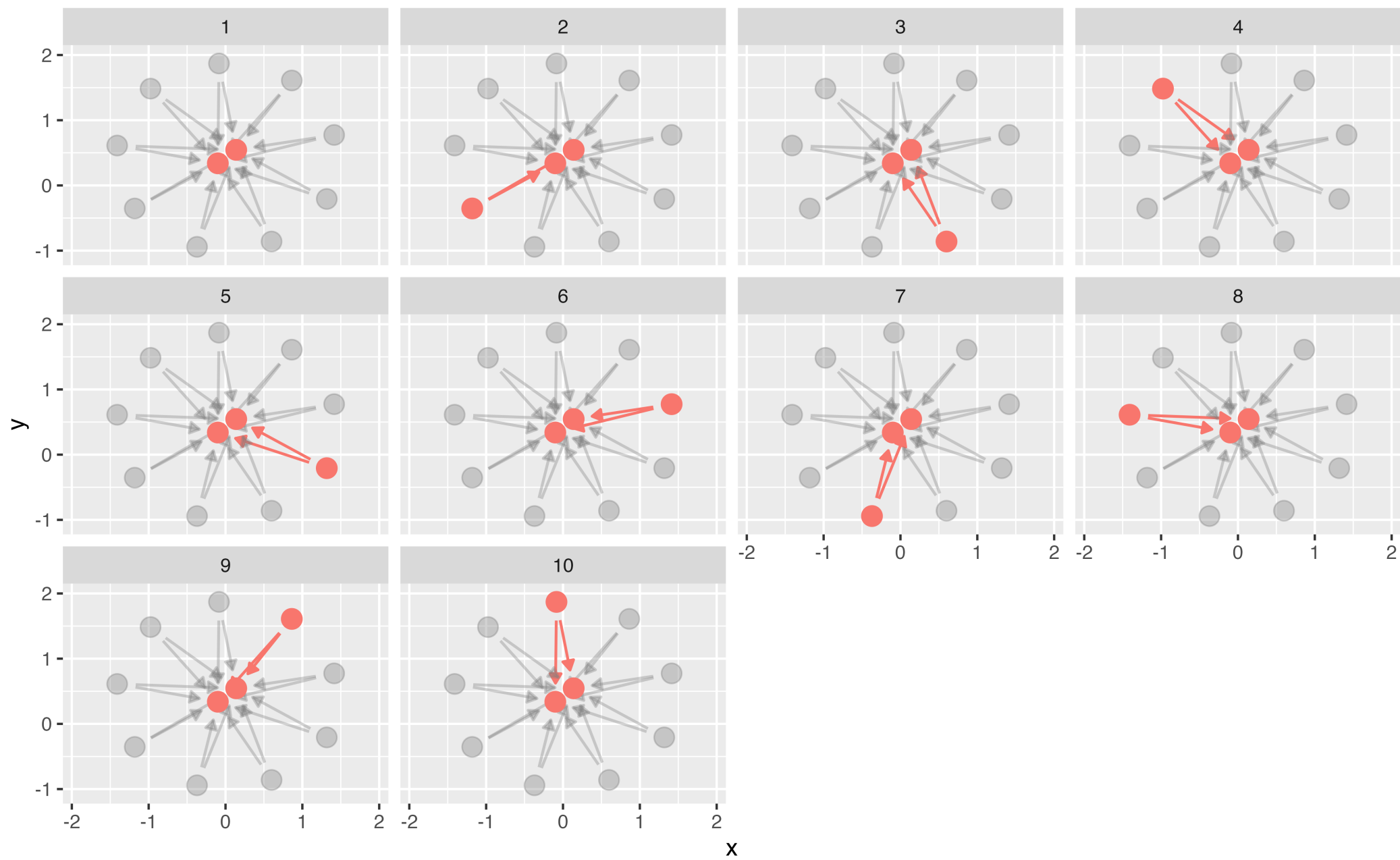
We want to know if $x \rightarrow y$...

But other paths also cause associations

ggdag_paths()

Identify “backdoor” paths

```
1 ggdag_paths(smk_wt_dag)
```



Your Turn 2

Call `tidy_dagitty()` on `coffee_cancer_dag` to create a tidy DAG, then pass the results to `dag_paths()`. What's different about these data?

Plot the open paths with `ggdag_paths()`. (Just give it `coffee_cancer_dag` rather than using `dag_paths()`; the quick plot function will do that for you.) Remember, since we assume there is *no* causal path from coffee to lung cancer, any open paths must be confounding pathways.

Your Turn 2

```
1 coffee_cancer_dag |>
2   tidy_dagitty() |>
3   dag_paths()
```

```
# A DAG with 4 nodes and 3 edges
```

```
#
```

```
# Exposure: coffee
```

```
# Outcome: cancer
```

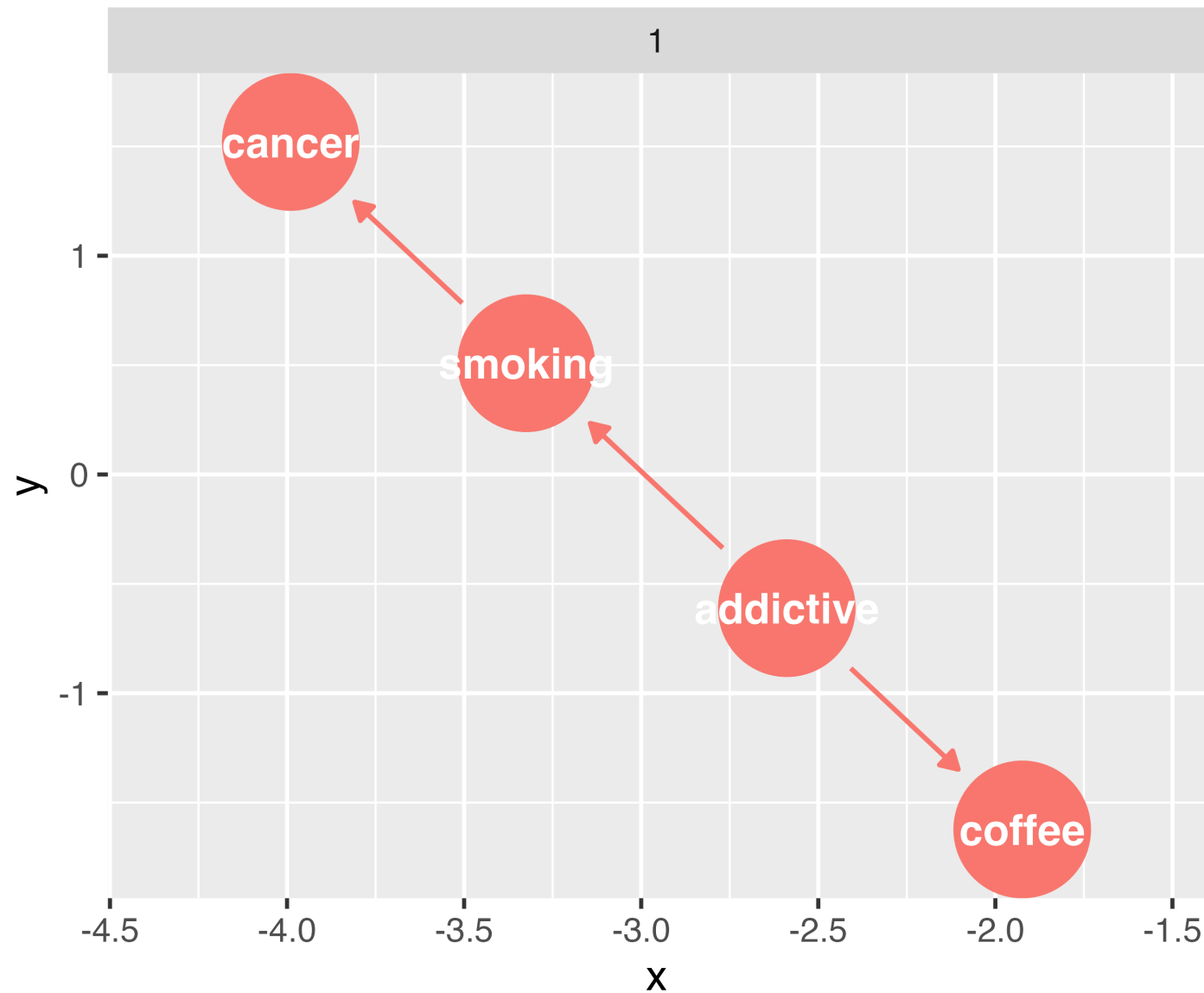
```
#
```

```
# A tibble: 5 × 11
```

	set	name	x	y	direction	to	xend	yend
	<chr>	<chr>	<dbl>	<dbl>	<fct>	<chr>	<dbl>	<dbl>
1	1	addictive	0.494	2.00	->	coff...	-0.423	2.81
2	1	addictive	0.494	2.00	->	smok...	1.50	1.11
3	1	cancer	2.41	0.310	<NA>	<NA>	NA	NA
4	1	coffee	-0.423	2.81	<NA>	<NA>	NA	NA
5	1	smoking	1.50	1.11	->	canc...	2.41	0.310

```
" 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197 198 199 200 201 202 203 204 205 206 207 208 209 210 211 212 213 214 215 216 217 218 219 220 221 222 223 224 225 226 227 228 229 230 231 232 233 234 235 236 237 238 239 240 241 242 243 244 245 246 247 248 249 250 251 252 253 254 255 256 257 258 259 260 261 262 263 264 265 266 267 268 269 270 271 272 273 274 275 276 277 278 279 280 281 282 283 284 285 286 287 288 289 290 291 292 293 294 295 296 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340 341 342 343 344 345 346 347 348 349 350 351 352 353 354 355 356 357 358 359 360 361 362 363 364 365 366 367 368 369 370 371 372 373 374 375 376 377 378 379 380 381 382 383 384 385 386 387 388 389 390 391 392 393 394 395 396 397 398 399 400 401 402 403 404 405 406 407 408 409 410 411 412 413 414 415 416 417 418 419 420 421 422 423 424 425 426 427 428 429 430 431 432 433 434 435 436 437 438 439 440 441 442 443 444 445 446 447 448 449 450 451 452 453 454 455 456 457 458 459 460 461 462 463 464 465 466 467 468 469 470 471 472 473 474 475 476 477 478 479 480 481 482 483 484 485 486 487 488 489 490 491 492 493 494 495 496 497 498 499 500 501 502 503 504 505 506 507 508 509 510 511 512 513 514 515 516 517 518 519 520 521 522 523 524 525 526 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1821 1822 1823 1824 1825 1826 1827 1828 1829 1830 1831 1832 1833 1834 1835 1836 1837 1838 1839 1840 1841 1842 1843 1844 1845 1846 1847 1848 1849 1850 1851 1852 1853 1854 1855 1856 1857 1858 1859 1860 1861 1862 1863 1864 1865 1866 1867 1868 1869 1870 1871 1872 1873 1874 1875 1876 1877 1878 1879 1880 1881 1882 1883 1884 1885 1886 1887 1888 1889 1890 1891 1892 1893 1894 1895 1896 1897 1898 1899 1900 1901 1902 1903 1904 1905 1906 1907 1908 1909 1910 1911 1912 1913 1914 1915 1916 1917 1918 1919 1920 1921 1922 1923 1924 1925 1926 1927 1928 1929 1930 1931 1932 1933 1934 1935 1936 1937 1938 1939 1940 1941 1942 1943 1944 1945 1946 1947 1948 1949 1950 1951 1952 1953 1954 1955 1956 1957 1958 1959 1960 1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024 2025 2026 2027 2028 2029 2030 2031 2032 2033 2034 2035 2036 2037 2038 2039 2040 2041 2042 2043 2044 2045 2046 2047 2048 2049 2050 2051 2052 2053 2054 2055 2056 2057 2058 2059 2060 2061 2062 2063 2064 2065 2066 2067 2068 2069 2070 2071 2072 2073 2074 2075 2076 2077 2078 2079 2080 2081 2082 2083 2084 2085 2086 2087 2088 2089 2090 2091 2092 2093 2094 2095 2096 2097 2098 2099 2100 2101 2102 2103 2104 2105 2106 2107 2108 2109 2110 2111 2112 2113 2114 2115 2116 2117 2118 2119 2120 2121 2122 2123 2124 2125 2126 2127 2128 2129 2130 2131 2132 2133 2134 2135 2136 2137 2138 2139 2140 2141 2142 2143 2144 2145 2146 2147 2148 2149 2150 2151 2152 2153 2154 2155 2156 2157 2158 2159 2160 2161 2162 2163 2164 2165 2166 2167 2168 2169 2170 2171 2172 2173 2174 2175 2176 2177 2178 2179 2180 2181 2182 2183 2184 2185 2186 2187 2188 2189 2190 2191 2192 2193 2194 2195 2196 2197 2198 2199 2200 2201 2202 2203 2204 2205 2206 2207 2208 2209 2210 2211 2212 2213 2214 2215 2216 2217 2218 2219 2220 2221 2222 2223 2224 2225 2226 2227 2228 2229 2230 2231 2232 2233 2234 2235 2236 2237 2238 2239 2240 2241 2242 2243 2244 2245 2246 2247 2248 2249 2250 2251 2252 2253 2254 2255 2256 2257 2258 2259 2260 2261 2262 2263 2264 2265 2266 2267 2268 2269 2270 2271 2272 2273 2274 2275 2276 2277 2278 2279 2280 2281 2282 2283 2284 2285 2286 2287 2288 2289 2290 2291 2292 2293 2294 2295 2296 2297 2298 2299 2300 2301 2302 2303 2304 2305 2306 2307 2308 2309 2310 2311 2312 2313 2314 2315 2316 2317 2318 2319 2320 2321 2322 2323 2324 2325 2326 2327 2328 2329 2330 2331 2332 2333 2334 2335 2336 2337 2338 2339 2340 2341 2342 2343 2344 2345 2346 2347 2348 2349 2350 2351 2352 2353 2354 2355 2356 2357 2358 2359 2360 2361 2362 2363 2364 2365 2366 2367 2368 2369 2370 2371 2372 2373 2374 2375 2376 2377 2378 2379 2380 2381 2382 2383 2384 2385 2386 2387 2388 2389 2390 2391 2392 2393 2394 2395 2396 2397 2398 2399 2400 2401 2402 2403 2404 2405 2406 2407 2408 2409 2410 2411 2412 2413 2414 2415 2416 2417 2418 2419 2420 2421 2422 2423 2424 2425 2426 2427 2428 2429 2430 2431 2432 2433 2434 2435 2436 2437 2438 2439 2440 2441 2442 2443 2444 2445 2446 2447 2448 2449 2450 2451 2452 2453 2454 2455 2456 2457 2458 2459 2460 2461 2462 2463 2464 2465 2466 2467 2468 2469 2470 2471 2472 2473 2474 2475 2476 2477 2478 2479 2480 2481 2482 2483 2484 2485 2486 2487 2488 2489 2490 2491 2492 2493 2494 2495 2496 2497 2498 2499 2500 2501 2502 2503 2504 2505 2506 2507 2508 2509 2510 2511 2512 2513 2514 2515 2516 2517 2518 2519 2520 2521 2522 
```

```
1 coffee_cancer_dag |>  
2   ggdag_paths()
```



path



open path

Closing backdoor paths

We need to account for these open, non-causal paths

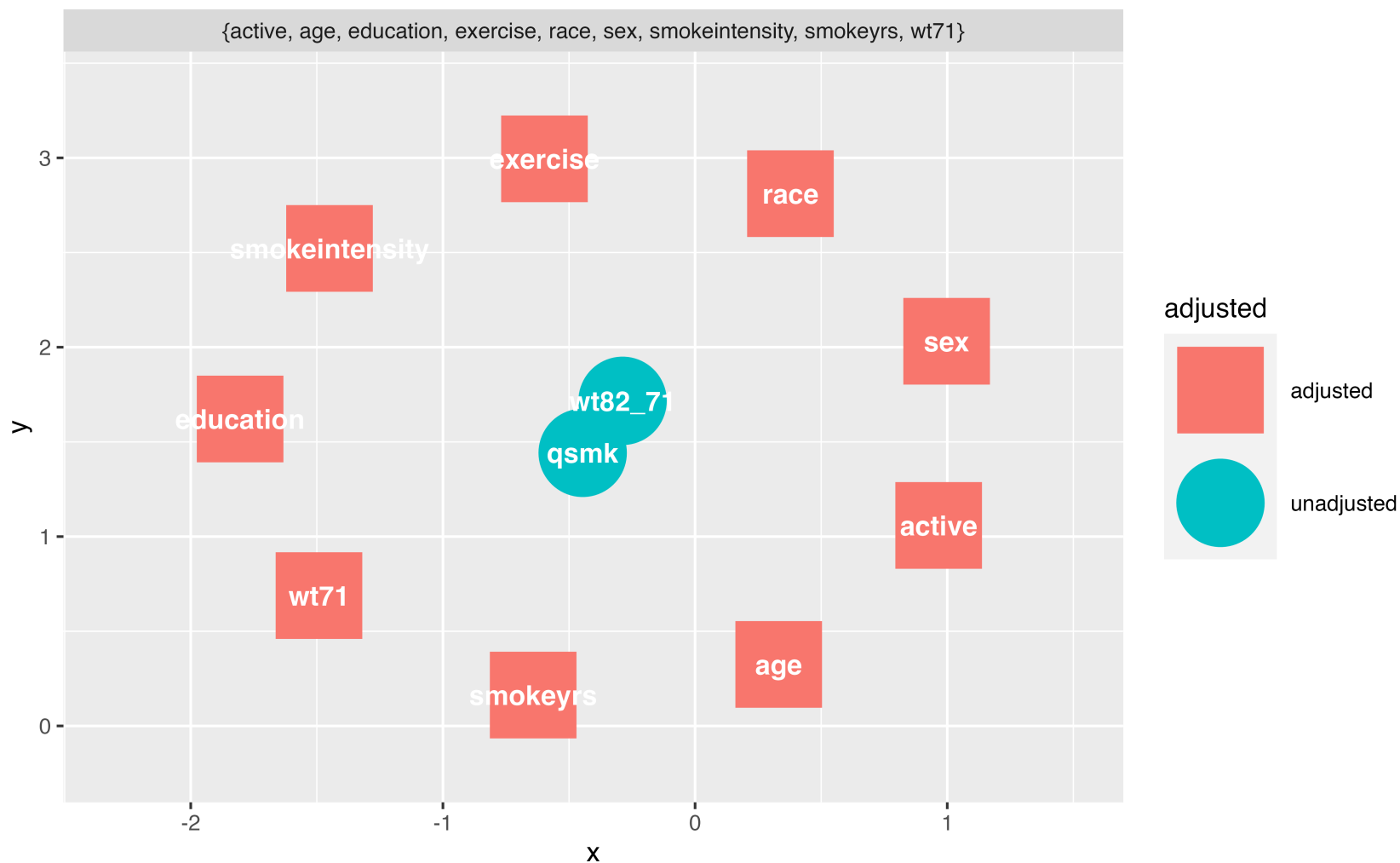
Randomization

Stratification, adjustment, weighting, matching, etc.

Identifying adjustment sets

```
1 ggdag_adjustment_set(smkn_wt_dag)
```


Identifying adjustment sets



Identifying adjustment sets

```
1 library(dagitty)
2 adjustmentSets(smkn_wt_dag)
```

```
{ active, age, education, exercise, race, sex, smokeintensity,  
  smokeyrs, wt71 }
```

Your Turn 3

Now that we know the open, confounding pathways (sometimes called “backdoor paths”), we need to know how to close them! First, we’ll ask {ggdag} for adjustment sets, then we would need to do something in our analysis to account for at least one adjustment set (e.g. multivariable regression, weighting, or matching for the adjustment sets).

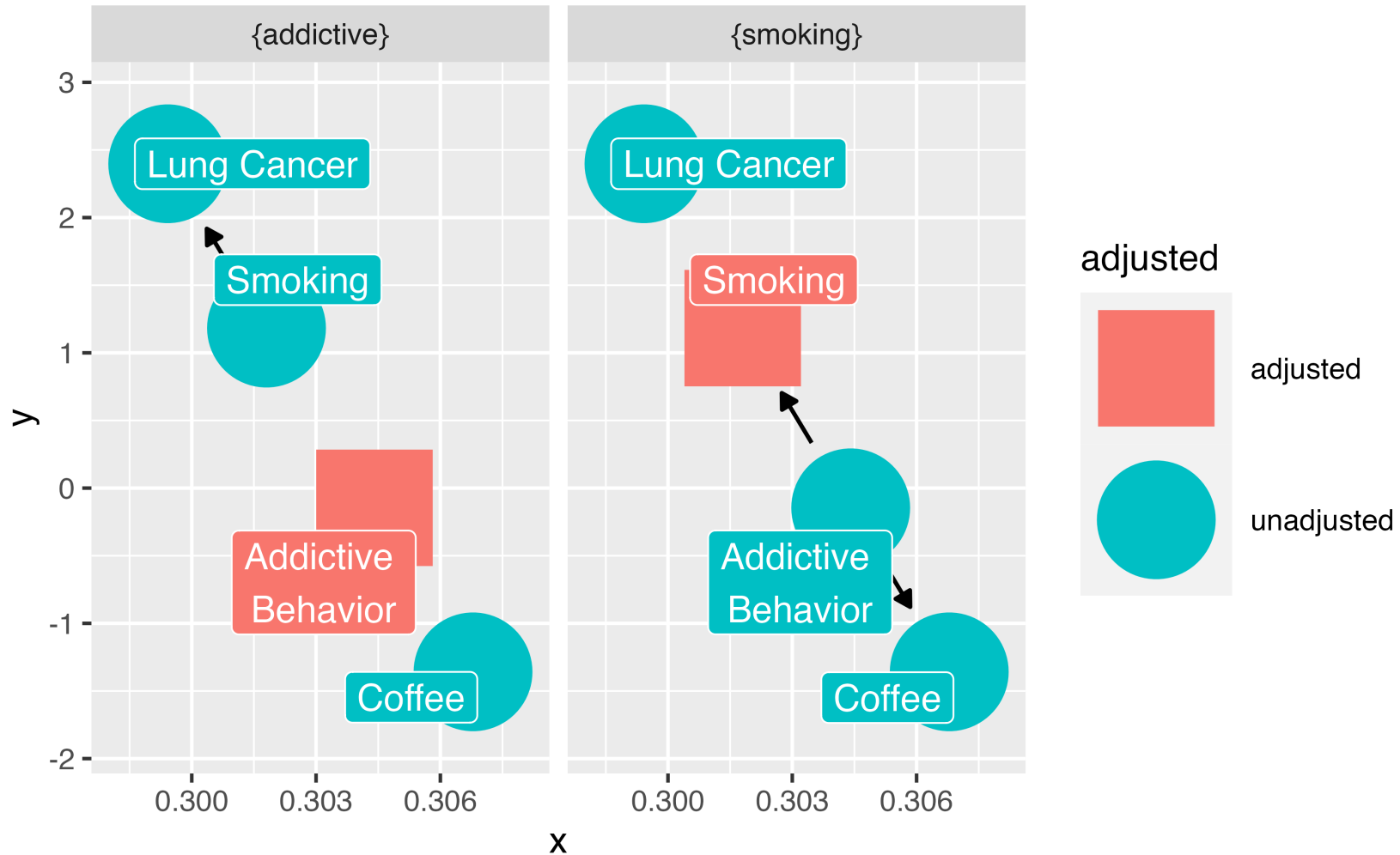
Use `ggdag_adjustment_set()` to visualize the adjustment sets. Add the arguments `use_labels = "label1"` and `text = FALSE`.

Write an R formula for each adjustment set, as you might if you were fitting a model in `lm()` or `glm()`

Your Turn 3

```
1 ggdag_adjustment_set(  
2   coffee_cancer_dag,  
3   use_labels = "label",  
4   text = FALSE  
5 )
```

Your Turn 3



Your Turn 3

- 1 cancer ~ coffee + addictive
- 2 cancer ~ coffee + smoking

Let's prove it!

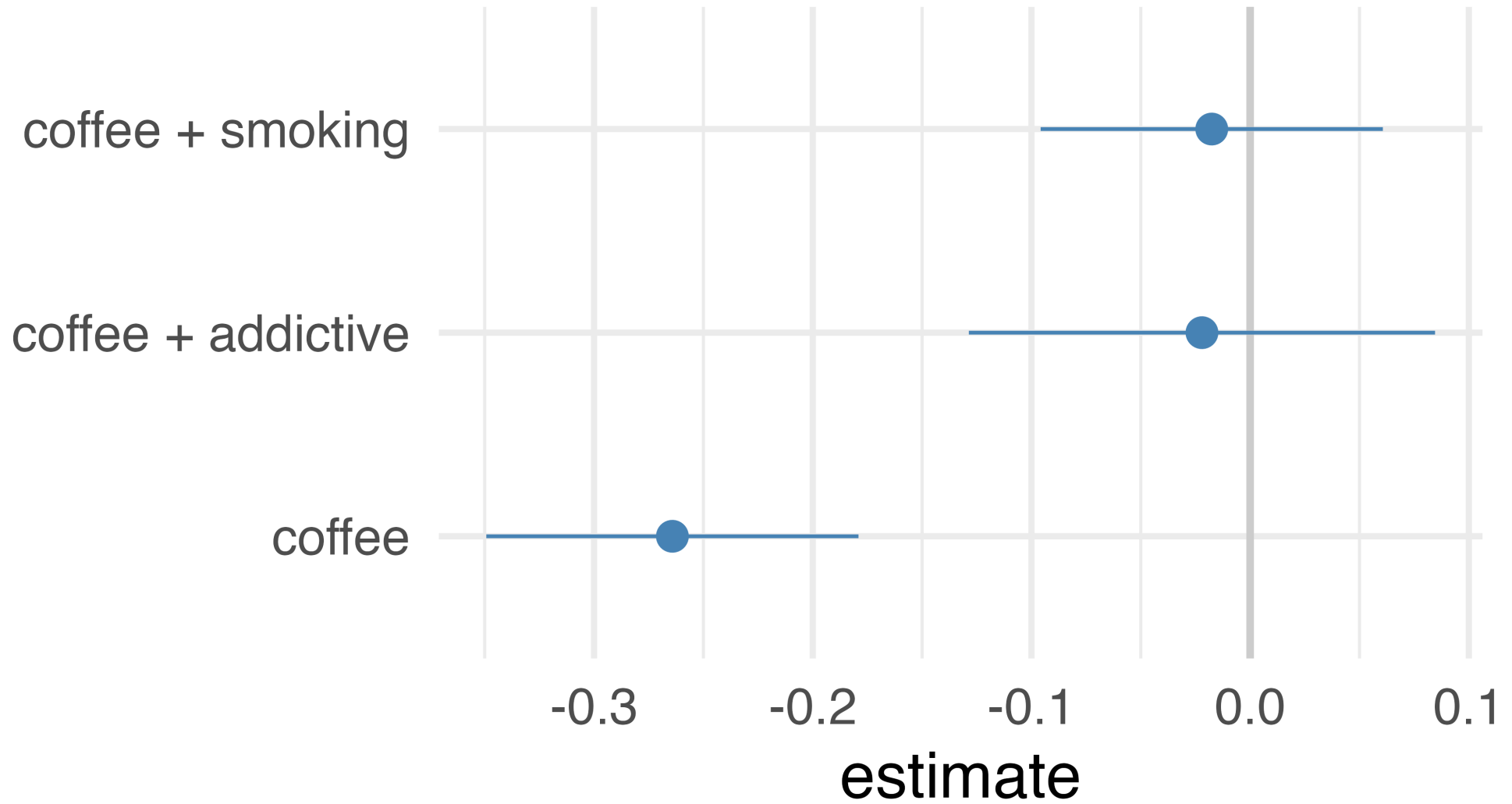
```
1 set.seed(1234)
2 dag_data <- coffee_cancer_dag |>
3   simulate_data(-.6)
```

Let's prove it!

```
1 dag_data
```

```
# A tibble: 500 × 4
  addictive cancer coffee smoking
  <dbl>    <dbl>   <dbl>   <dbl>
1    0.569    3.11  -0.326  -1.29
2    0.411    1.52   0.330  -1.57
3    1.20     1.06  -0.557  -2.40
4   -0.782   -0.504 -0.148   0.376
5    0.0357  -0.709 -0.342  -1.53
6    1.96     1.05  -1.90  -0.823
7    1.13     0.211 -0.581  -0.534
8    0.697    0.892 -1.36   -0.267
9   -0.779    0.748  0.455   0.302
10   -1.13    0.930  0.568   0.742
" . . . . ."
```


Let's prove it!



correct effect size: 0

Choosing what variables to include

Adjustment sets and domain knowledge

Conduct sensitivity analysis if you don't have something important

Common trip ups

Using prediction metrics

The 10% rule

Predictors of the outcome, predictors of the exposure

Selection bias and colliders (more later!)

Resources: ggdag vignettes

An Introduction to ggdag

An Introduction to Directed Acyclic Graphs

Common Structures of Bias

