*These notes summarise selected lecture concepts and are not a substitute for working through the lecture slides, tutorials, and self-study exercises. Feel free to personalise and develop them into your own summary sheet.*

**Causal DAGs** — Causal DAGs are DAGs where the arrows are assumed to represent a causal direction.

**Graph surgery** — Intervening on variable $x_k$ removes all incoming arrows into the node and makes it a root variable.

**Postinterventional distribution** — Assume we intervene on $x_k$ by setting $x_k \sim p'(x_k)$ for intervention distribution (randomisation scheme) $p'$. The resulting distribution is $p(\mathbf{x}; do(x_k) \sim p') = \prod_{i \neq k} p(x_i|\text{pa}_i) \cdot p'(x_k)$

**Atomic interventions** — Atomic interventions correspond to using a point mass for $p'(x_k)$, setting $x_k$ to a fixed value, e.g. $a$. Notation for the postinterventional distr: $p(\mathbf{x}; do(x_k) = a)$

**Inverse probability weighting** — A method to turn observational data $\mathbf{x}^{(i)} \sim p(\mathbf{x})$ into samples from $p(\mathbf{x}; do(x_k) \sim p')$ by reweighting each $\mathbf{x}^{(i)}$ with $w^{(i)} = p'(x_k^{(i)})/p(x_k^{(i)}|\text{pa}_k^{(i)})$.

**Adjustment for direct causes** — A method to compute how intervening on $x_k$ changes the distribution of $x_i$:

$$p(x_i; do(x_k) \sim p') = \mathbb{E}_{p(\text{pa}_k)p'(x_k)}\left[p(x_i|x_k, \text{pa}_k)\right] \qquad p(x_i; do(x_k) = a) = \mathbb{E}_{p(\text{pa}_k)}\left[p(x_i|x_k = a, \text{pa}_k)\right]$$

**Backdoor paths** — A backdoor path from $x$ to $y$ is any (undirected) path that begins with an arrow into $x$, typically transmitting spurious association via common causes rather than the causal effect of $x$ on $y$. Open backdoor paths generally make the conditional and postinterventional distribution different.

**Action/observation exchange** — Let $G_{\underline{x_k}}$ be the graph where all outgoing arrows from $x_k$ are removed. If $x_i \perp\!\!\!\perp x_k|\mathbf{z}$ in $G_{\underline{x_k}}$ then $p(x_i|\mathbf{z}; do(x_k) = a) = p(y|\mathbf{z}, x_k = a)$

**Backdoor adjustment** — This is a method that generalises the adjustment for directed causes. If $\mathbf{z}$ satisfies (1) $x_i \perp\!\!\!\perp x_k|\mathbf{z}$ in $G_{\underline{x_k}}$ (2) no component of $\mathbf{z}$ is a descendant of $x_k$, then $p(x_i; do(x_k) = a) = \mathbb{E}_{p(\mathbf{z})}\left[p(x_i|x_k = a, \mathbf{z})\right]$.