# *Speak math*

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Learn the notation. We will use math notation to design and specify our models. There are two benefits with this: it's explicit and easy to translate to code. Chapter 4 in the book goes through a first example of how to design a model, how to sample from it, and how to extend it.

Greek letters are used to show that it is a parameter we want to estimate. Yes, you will learn how to pronounce many Greek letters.

We differ between two things in our models: outcome and predictor. An outcome is what we try to model. We want to predict the outcome. Often we use predictors in our models, i.e., things we believe influence the outcome (pp. 93 is key to this chapter). The chapter goes through a complete example where we do prior and posterior predictive checks and learn to plot things. Later in the chapter McElreath introduces polynomials (which we avoid) and splines (which we can use if we must).

These two concepts will **not** be stressed in this course.

The simple linear regression model, a framework for estimating the association between a predictor variable and an outcome variable, is the basis we will stand on in this course.

Spurious associations give rise to very many funky things. We use directed acyclic graphs to interpret these associations. These graphs comes in different patterns and depending on the patterns we get different conditional independencies, i.e., testable implications. We want to use this approach for multiple regression (i.e., having $> 1$ predictor). Carefully thinking about what variables to include as predictors will save us later down the road (i.e., included variable bias). The example in the book introduces $> 1$ predictors, so we can argue over which predictors should be included in a model.

Spurious can be translated to 'fake'.

By plotting things you will be able to see how well the model does its job. Learn how to do predictor residual plots (the average prediction error when we use all of the other predictor variables to model a predictor of interest), posterior prediction plots (check the model's implied predictions against the observed data), and counterfactual plots (displays the causal implications of the model). Each has its purpose.

The concept of masked relationships is important to grasp. Basically it's about two predictors, where one influences the outcome positively and the other influences the outcome negatively.

We now also start using categorical variables, first by introducing binary categories (e.g., true/false, male/female, 0/1), then by introducing many categories.

DIRECTED ACYCLIC GRAPHS (DAGs) are wonderful to use when we want to reason about causality. It provides us with testable implications, which we can use to test if our model 'holds'.

In Chapter 6, a number of terms are introduced. *Non-identifiability* (the structure of the data and model does not make it possible to estimate a parameter), *collider bias* (adding a predictor induces statistical selection within the model), *multicollinearity* (strong association between two or more predictor variables, i.e., the multicollinear legs example), and *post-treatment bias* (the fungus example). The latter bias is the opposite of omitted variable bias, i.e., we worry about a variable we don't have access to, and is sometimes called included variable bias (i.e., we include variables to the model which *should not* be included).

In order to reason about the above terms we use DAGs. Four, and only four, elemental confounds exist in DAGs: fork, pipe, collider, and descendant. It's important to know when we *should* and *should not* condition on a variable. i.e., include it in the model. Understand the *backdoor criterion*!

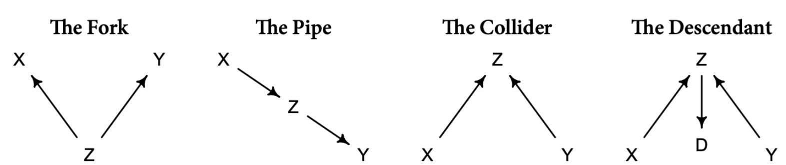


Figure 1: The four elemental confounds in DAGs.

Finally, a list of Greek characters and their pronunciation.

| Character | Name | Character | Name |
|---|---|---|---|
| $\alpha$ | alpha *AL-fuh* | $\nu$ | nu *NEW* |
| $\beta$ | beta *BAY-tuh* | $\xi$, $\Xi$ | xi *KSIGH* |
| $\gamma$, $\Gamma$ | gamma *GAM-muh* | o | omicron *OM-uh-CRON* |
| $\delta$, $\Delta$ | delta *DEL-tuh* | $\pi$, $\Pi$ | pi *PIE* |
| $\epsilon$ | epsilon *EP-suh-lon* | $\rho$ | rho *ROW* |
| $\zeta$ | zeta *ZAY-tuh* | $\sigma$, $\Sigma$ | sigma *SIG-muh* |
| $\eta$ | eta *AY-tuh* | $\tau$ | tau *TOW (as in cow)* |
| $\theta$, $\Theta$ | theta *THAY-tuh* | $\upsilon$, $\Upsilon$ | upsilon *OOP-suh-LON* |
| $\iota$ | iota *eye-OH-tuh* | $\phi$, $\Phi$ | phi *FEE, or FI (as in hi)* |
| $\kappa$ | kappa *KAP-uh* | $\chi$ | chi *KI (as in hi)* |
| $\lambda$, $\Lambda$ | lambda *LAM-duh* | $\psi$, $\Psi$ | psi *SIGH, or PSIGH* |
| $\mu$ | mu *MEW* | $\omega$, $\Omega$ | omega *oh-MAY-guh* |