Our goal for our cricket analysis, to define a metric
for the expected number of runs per 100 balls for a
player "p" in league "l" against a bowling style "t".

Define Y_{gb} as the number of runs scored on ball b in game
g, where $Y_{gb} \in \{0,1,2,4,6\}$. For the purposes of our analysis,
we will assume that no ball results in a 3 or 5. Because of
the complex distribution of the overall outcomes $\underset{\sim}{Y}$, we will
model the runs scored via a multinomial mixed effects model.
Specifically,

$$P(Y_{gb} = k) = \pi_{gbk}$$
$$\text{logit}(\pi_{gbk}) = \underset{\sim}{X}\underset{\sim}{\beta}_k + \underset{\sim}{Z}u_k$$

where $\underset{\sim}{X}$ and $\underset{\sim}{Z}$ are the matrices for the fixed and random effects,
respectively.

For the fixed effects, we can choose variables such as innings, runs needed to
win (if the second innings), wickets taken, balls remaining in innings etc.

For the random effects, define $u_{plt,k}$ as the random effect for scoring k runs on
a ball with player p in league l against a bowler with bowling style t.
A particular player more have more variability of scoring k runs in one
league vs. another league; therefore, we will place a distribution on these
random effects of

$$u_{plt,k} \sim N(0, \sigma^2_{l,k})$$

Because our ultimate goal is to project a players ability in a league they haven't
played in based on performance in other leagues, we need to account for
correlations between leagues. Therefore, we will say that in comparing player
p and bowling style t in leagues L and L', we say that

correlations between leagues, … in leagues l and l', we say that p and bowling style t

$$\mathrm{Cor}\left(u_{plt,k},\, u_{pl't,k}\right) = \rho_{ll';k}\,.$$

We can then use techniques to provide estimates of β_k, $\sigma^2_{l,k}$, and $\rho_{ll';k}$, and the predictors u_{plt} for players in leagues that are observable.

We can then Monte Carlo techniques to estimate u_{plt} for unobservable data (ie predict how player p would perform in league l).