

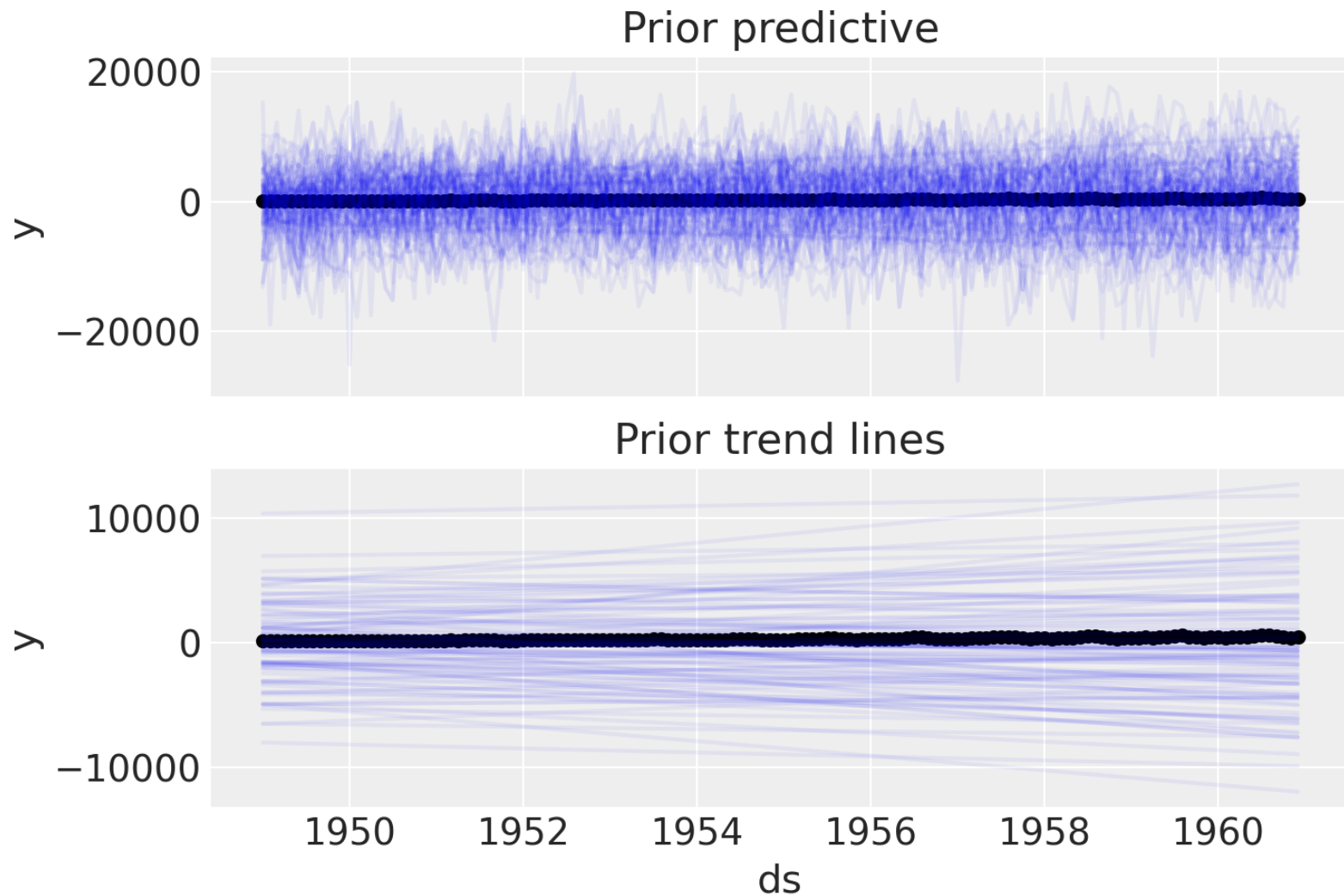
# Bayesian Statistics and Modeling

## Part II

# Time series modeling with `pymc3`

Based on [this example](#)

# Prior predictions (WHAT??)

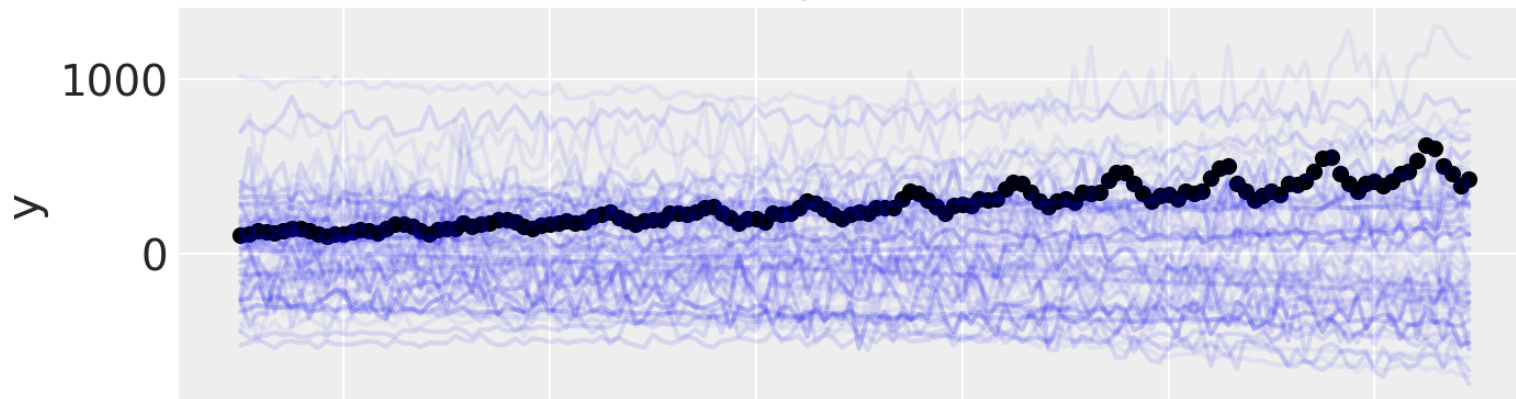


# Prior predictions (WHAT??)

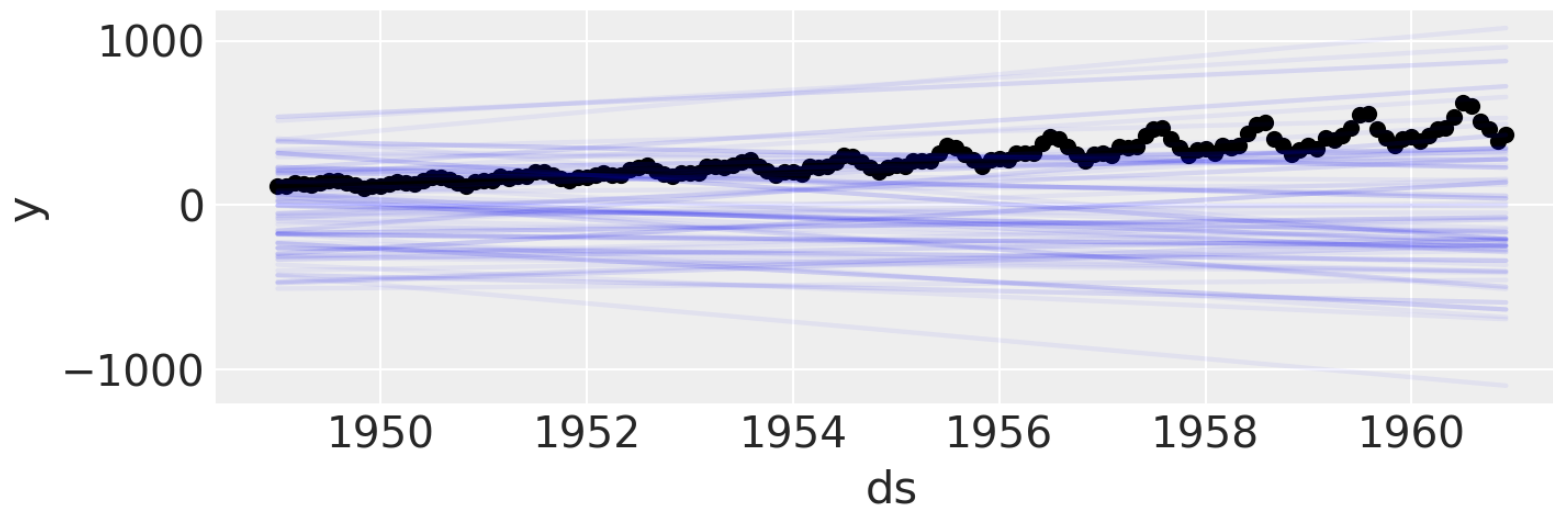
- Look at a large array of possible "reasonable" outcomes given our assumptions about the data
- Gives us an idea of whether our priors make sense
- In this case, we want to make some corrections

# Updated priors

Prior predictive



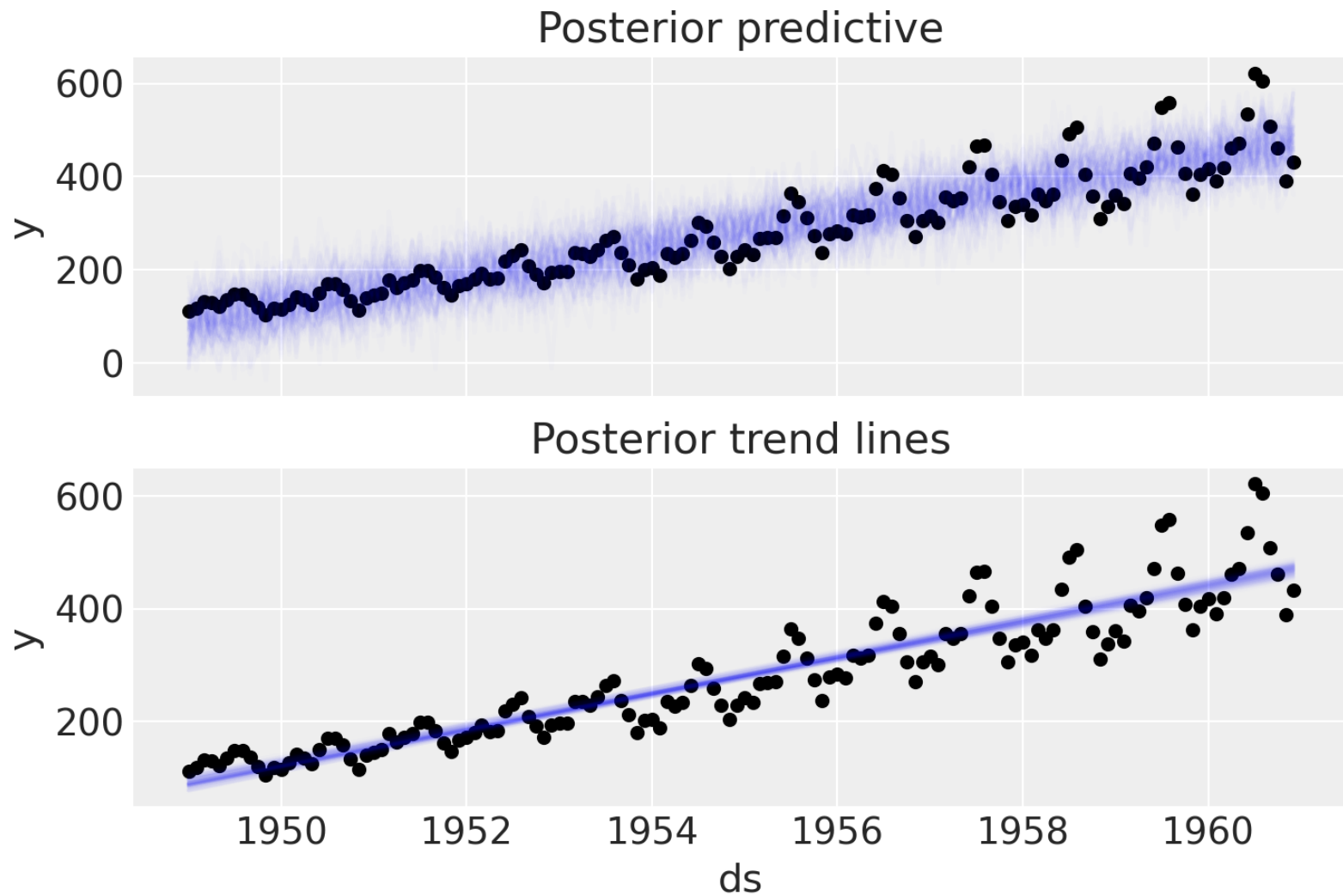
Prior trend lines



# Posterior predictions

- Incorporate our actual data and then compare our model to observed outcomes
- Decide if we think that our model can make reasonable predictions

# Posterior predictions

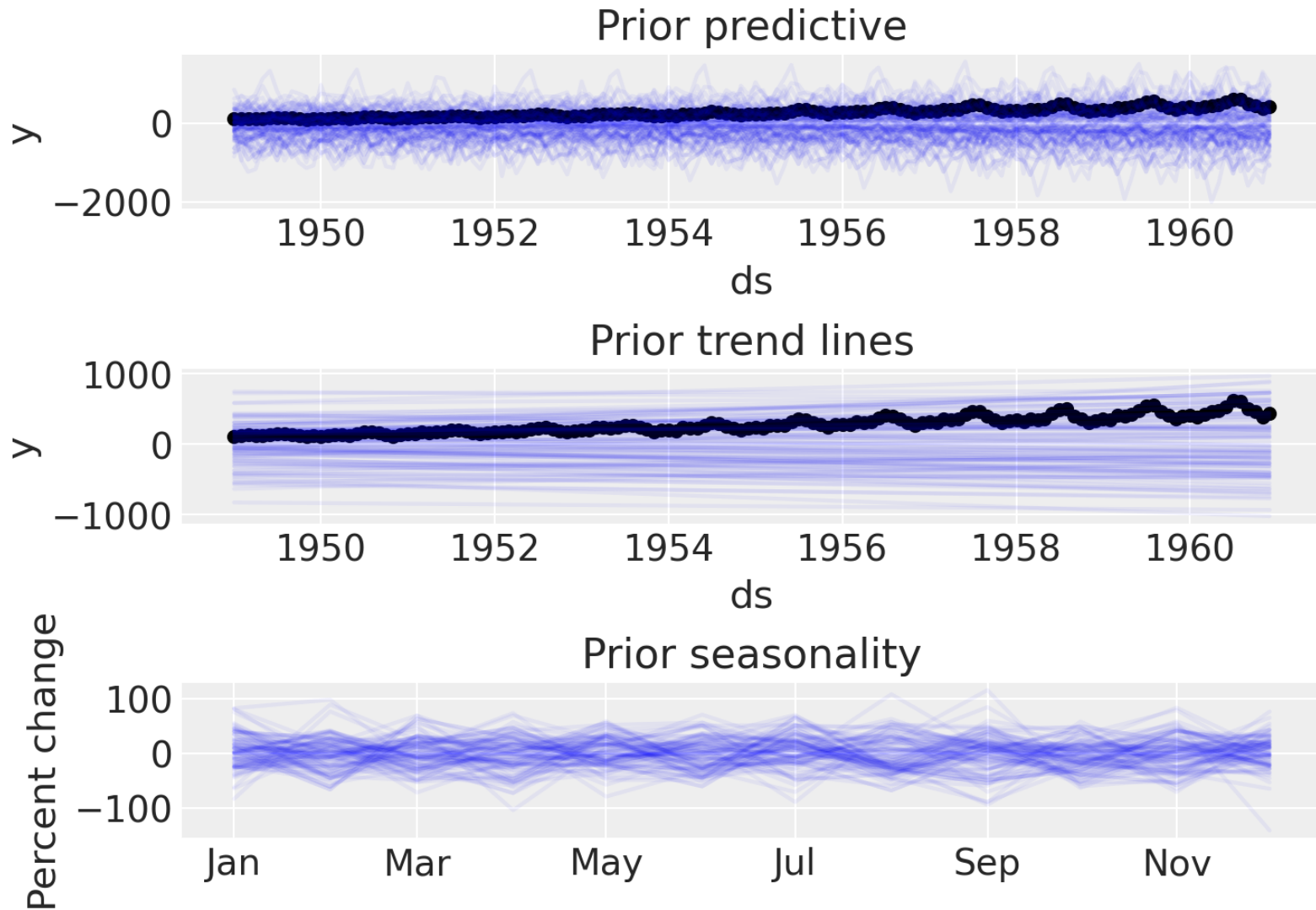


# Adding seasonality

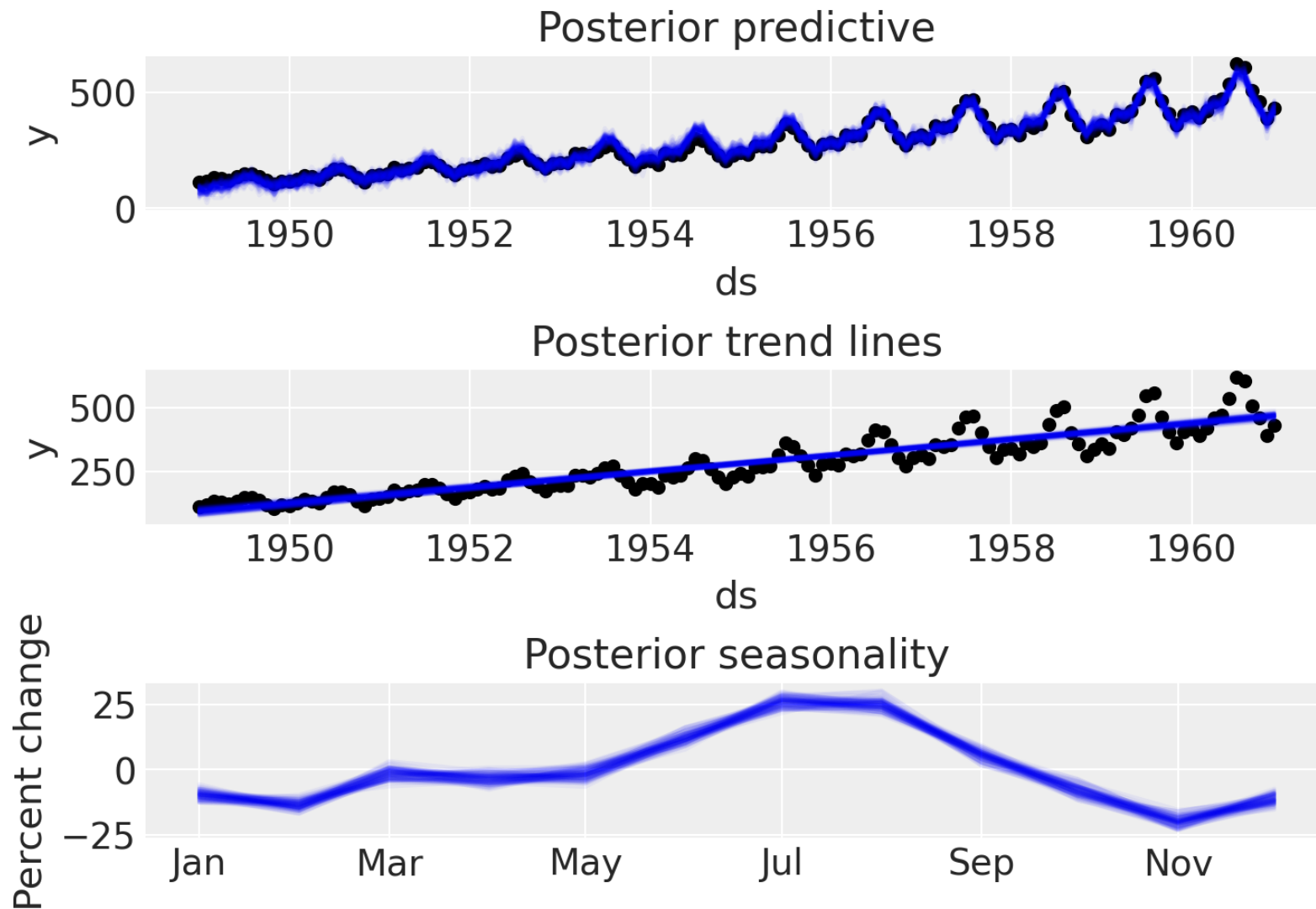
We add a group of periodic functions (fourier features) to function as our "seasonality splines" (if we think of our model as a GAM). They will get stretched or weighted based on observations.



# Seasonal priors

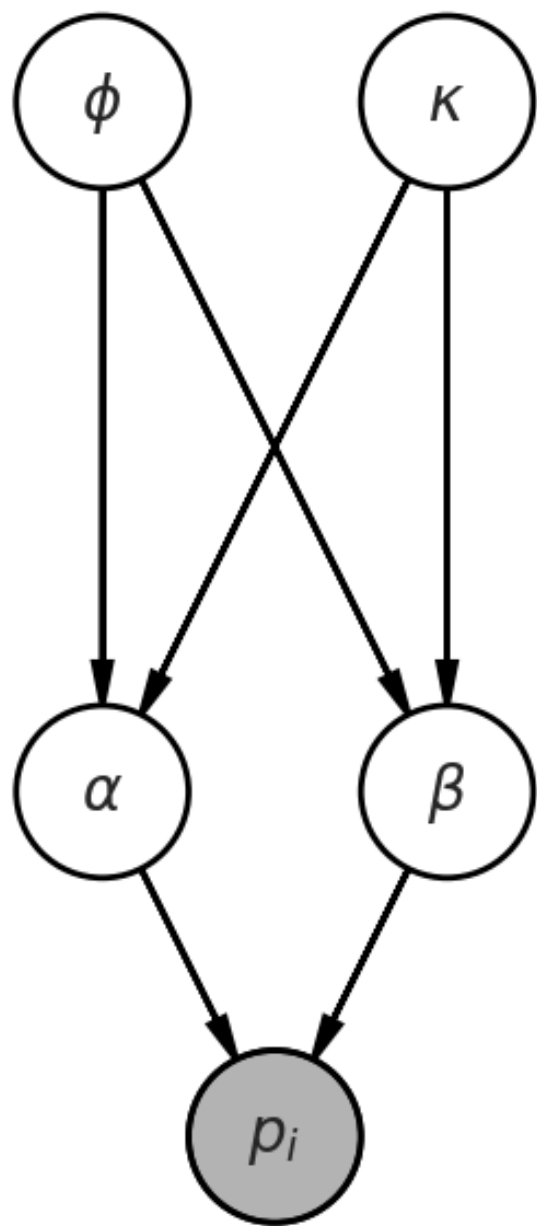


# Seasonal posteriors

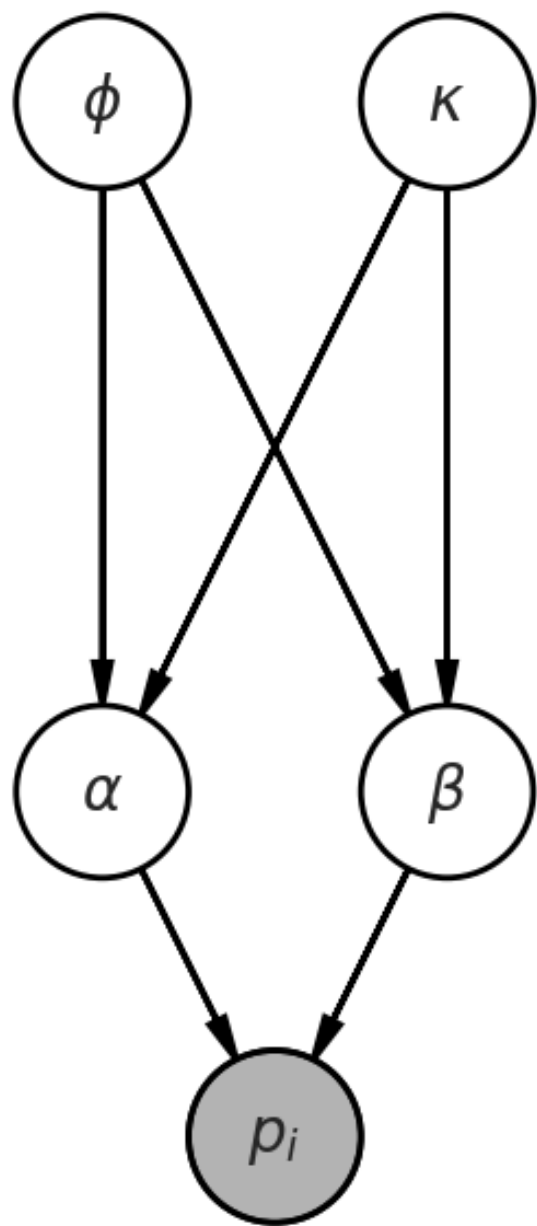


# Modeling baseball outcomes

A revised/updated version of [this tutorial](#)



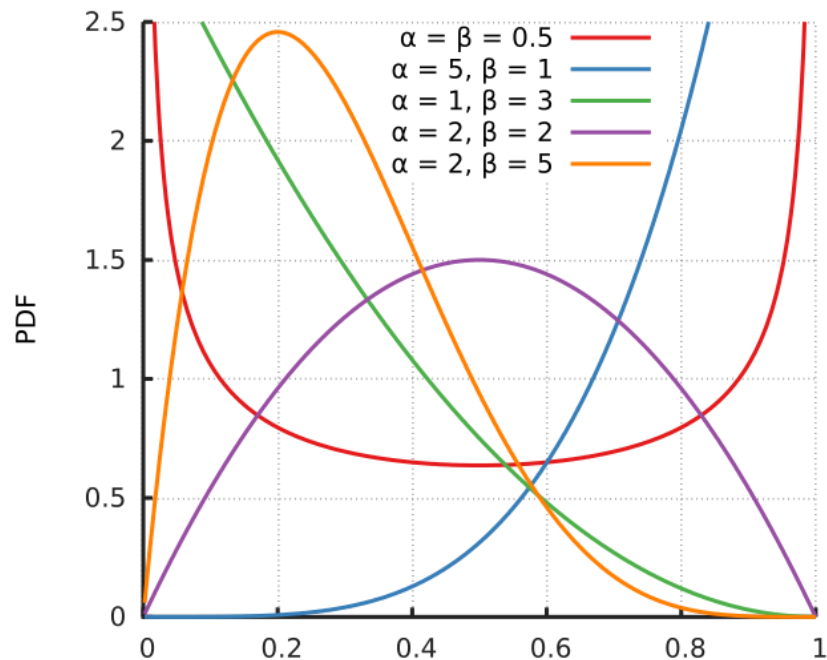
- $\phi$  (phi) - Our population-level expectation of batting average
- $\kappa$  (kappa) - Population variance in batting average
- $\alpha, \beta$  - Parameters of our beta distribution
- $p_i$  - Individual batting average



$$\alpha = \phi \cdot \kappa$$

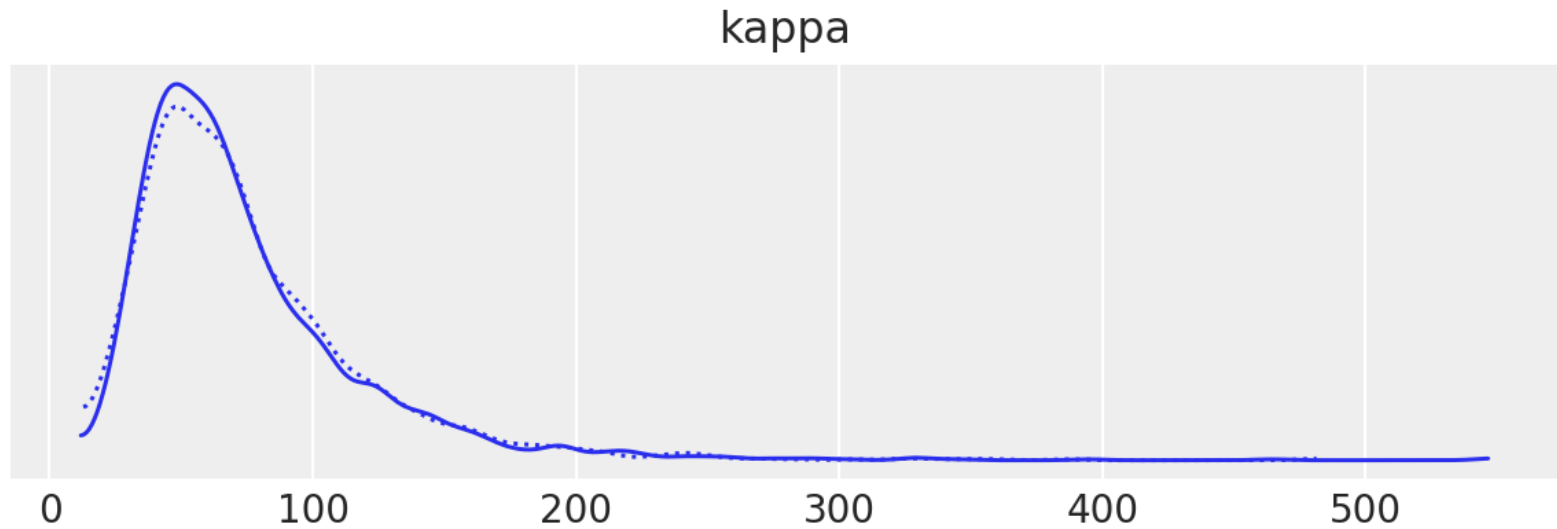
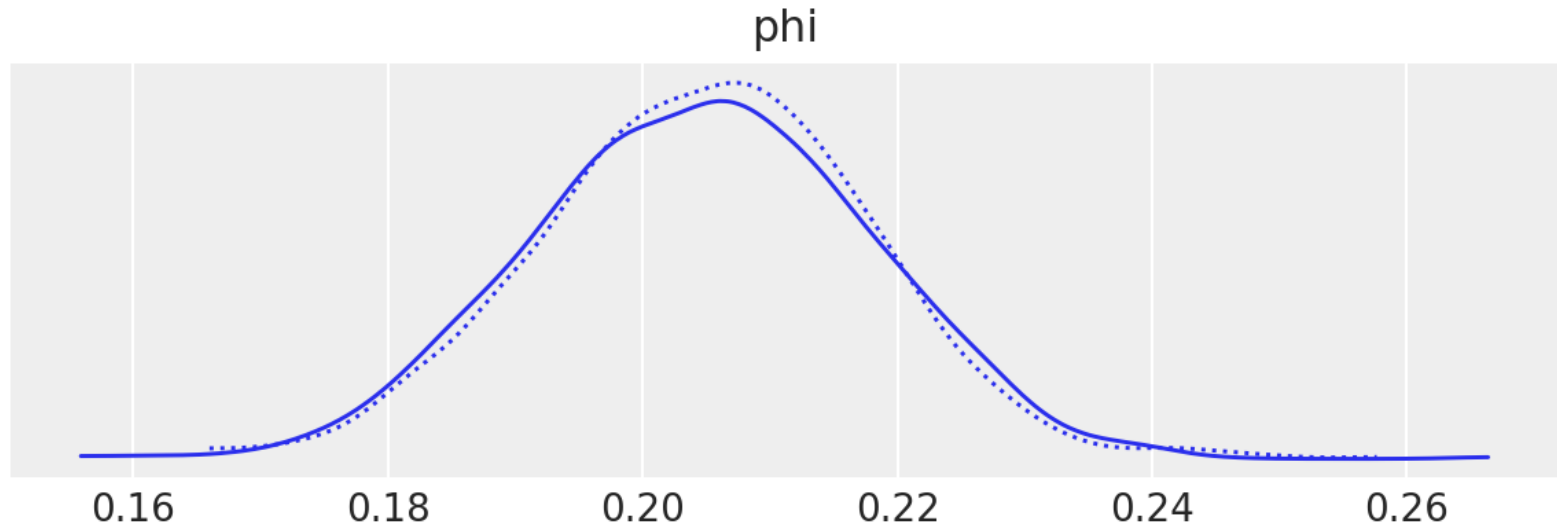
$$\beta = (1 - \phi) \cdot \kappa$$

# Beta distribution

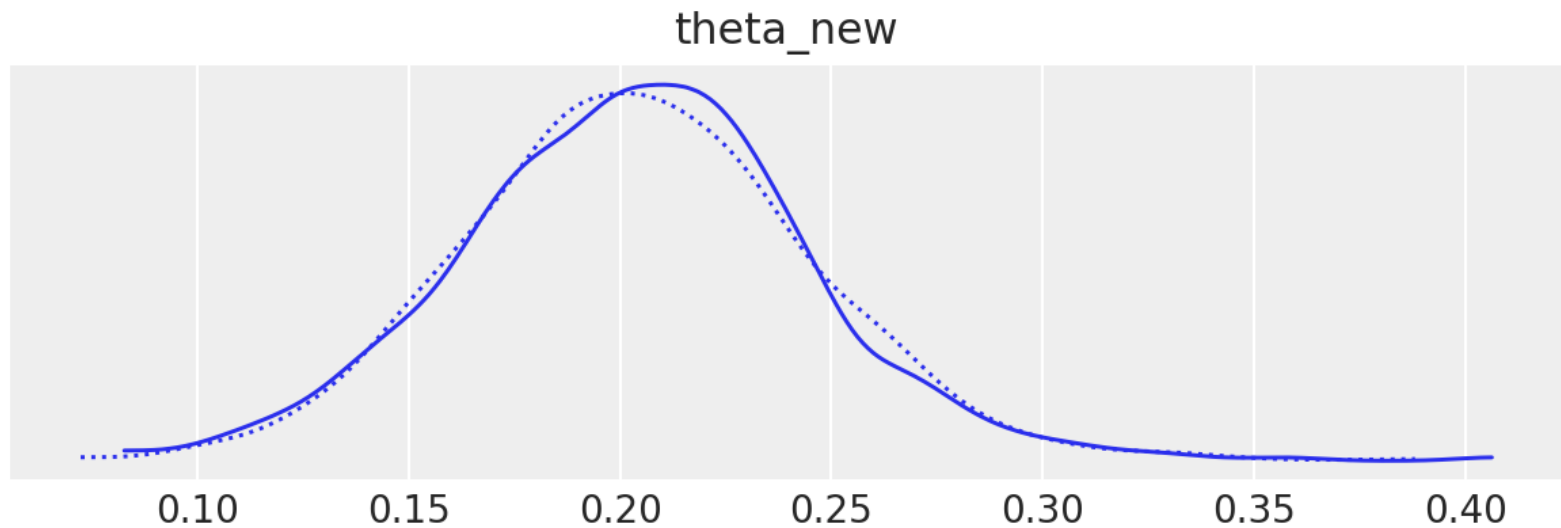


- Used where there are binary outcomes (hit or no hit)
- Tilts toward 1 or 0 based on observed outcomes and concentration of those outcomes

# Population values

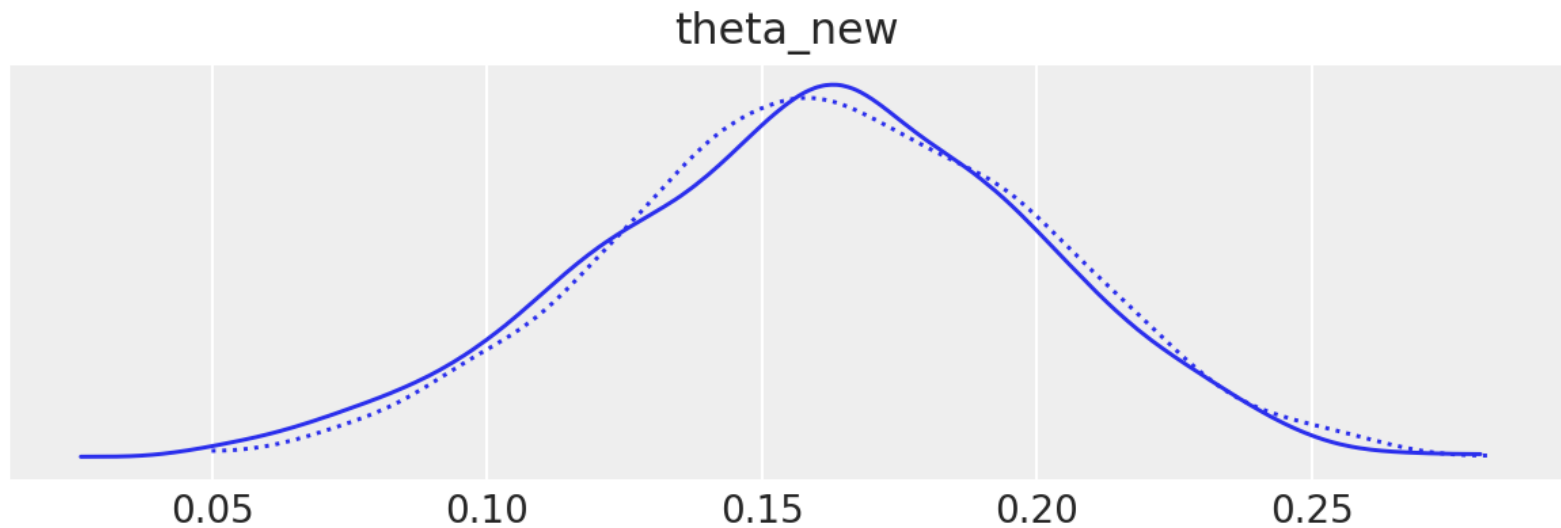


# Player with 4 at-bats, no hits

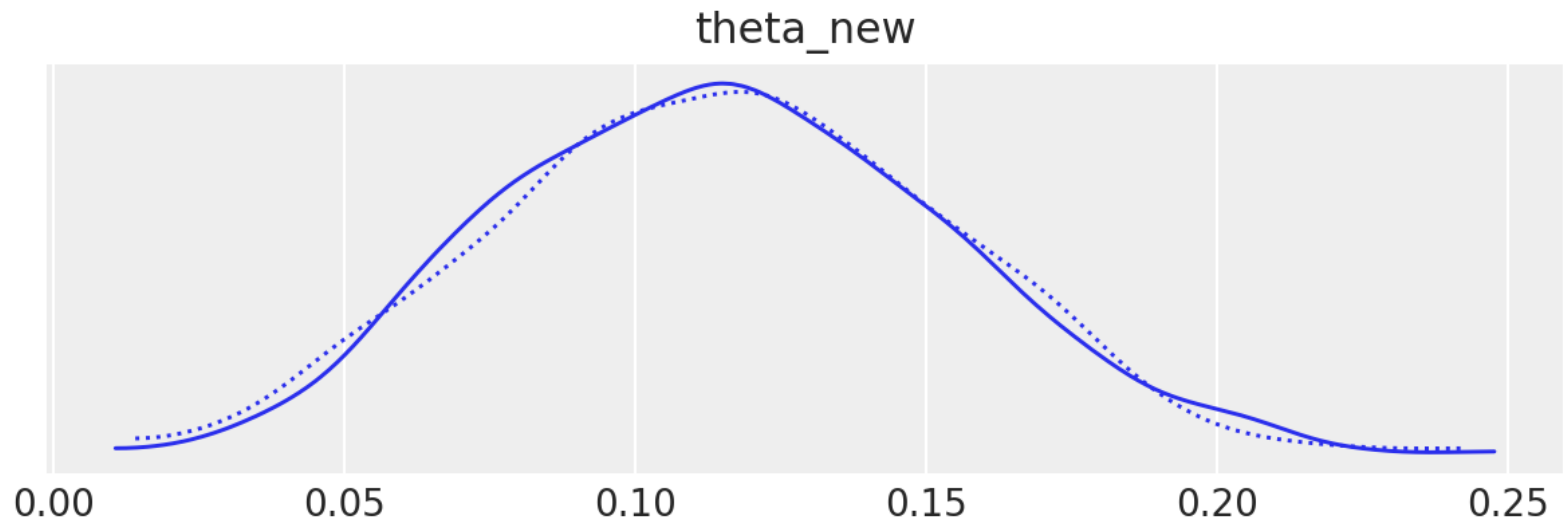




# Player with 25 at-bats, no hits



# Player with 50 at-bats, no hits



# Mariners 2021

