

Brand Tracking with Bayesian Models and Metaflow

Corrie Bartelheimer
Senior Data Scientist @ Latana

Berlin Bayesian, 10/11/2021

TIER



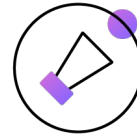
How many people have
heard of our brand?



How well known is the brand in target group?



How do people perceive the brand?

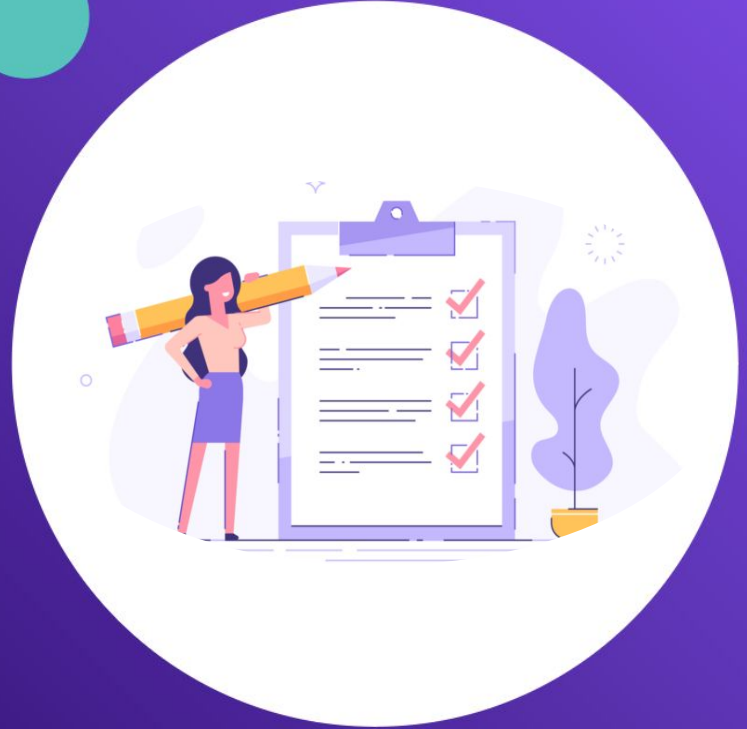


Have there been changes?

What makes Brand Tracking difficult?

Survey Problems

- Small target groups
- Signal or Noise?
- Representativeness of respondents



Traditional Approaches

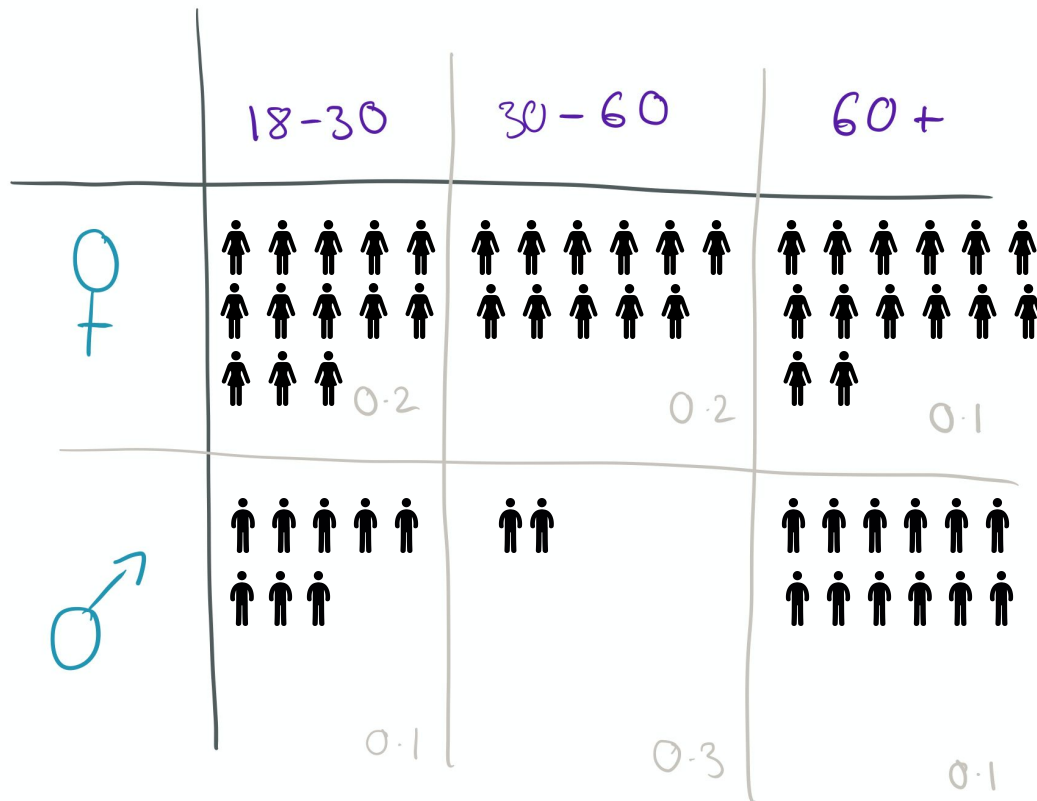
Weighting

	18-30	30-60	60+
♀			
♂			

Weighting

	18-30	30-60	60+
♀	0.2	0.2	0.1
♂	0.1	0.3	0.1

Weighting



Quota Sampling

	18-30	30-60	60+
♀	200	200	100
♂	100	300	100

Quota Sampling

	18-30	30-60	60+
♀	200	200	100
♂	100	300	100

Can take a while...

Introducing: Mr. P Multilevel Regression & Poststratification

Multilevel Regression

Multilevel Regression

knows brand $\sim \text{Bernoulli}(p)$

Multilevel Regression

knows brand $\sim \text{Bernoulli}(p)$

$$\text{logit}(p) = \alpha_{[\text{gender}]} + \beta_{[\text{age}]}$$

Multilevel Regression

$$\text{knows brand} \sim \text{Bernoulli}(p)$$

$$\text{logit}(p) = \alpha_{\text{gender}} + \beta_{\text{age}}$$

$$\alpha_{\text{gender}} \sim \text{Normal}(\mu_{\alpha}, \sigma_{\alpha})$$

$$\beta_{\text{age}} \sim \text{Normal}(\mu_{\beta}, \sigma_{\beta})$$

Multilevel Regression

$$\text{knows brand} \sim \text{Bernoulli}(p)$$

$$\text{logit}(p) = \alpha_{[\text{gender}]} + \beta_{[\text{age}]}$$

$$\alpha_{[\text{gender}]} \sim \text{Normal}(\mu_\alpha, \sigma_\alpha)$$

$$\beta_{[\text{age}]} \sim \text{Normal}(\mu_\beta, \sigma_\beta)$$

$$\mu_\alpha, \mu_\beta \sim \text{Normal}(0, 1)$$

$$\sigma_\alpha, \sigma_\beta \sim \text{Normal}_+(0, 1)$$

Multilevel Regression

knows brand $\sim \text{Bernoulli}(p)$

$$\text{logit}(p) = \alpha_{[\text{gender}]} + \beta_{[\text{age}]}$$

Multilevel

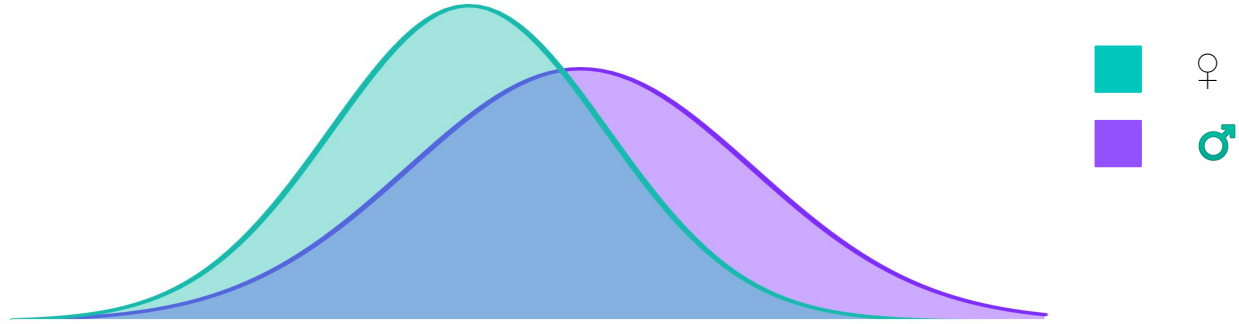
$$\alpha_{[\text{gender}]} \sim \text{Normal}(\mu_\alpha, \sigma_\alpha)$$

$$\beta_{[\text{age}]} \sim \text{Normal}(\mu_\beta, \sigma_\beta)$$

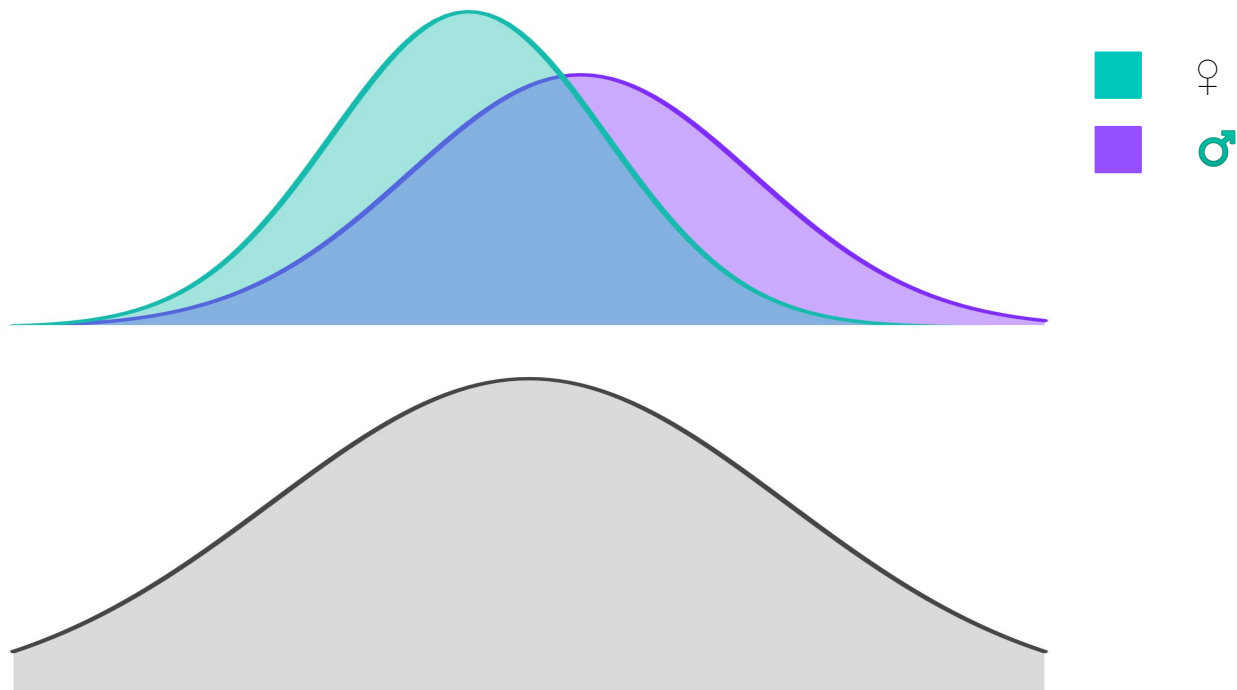
$$\mu_\alpha, \mu_\beta \sim \text{Normal}(0, 1)$$

$$\sigma_\alpha, \sigma_\beta \sim \text{Normal}_+(0, 1)$$

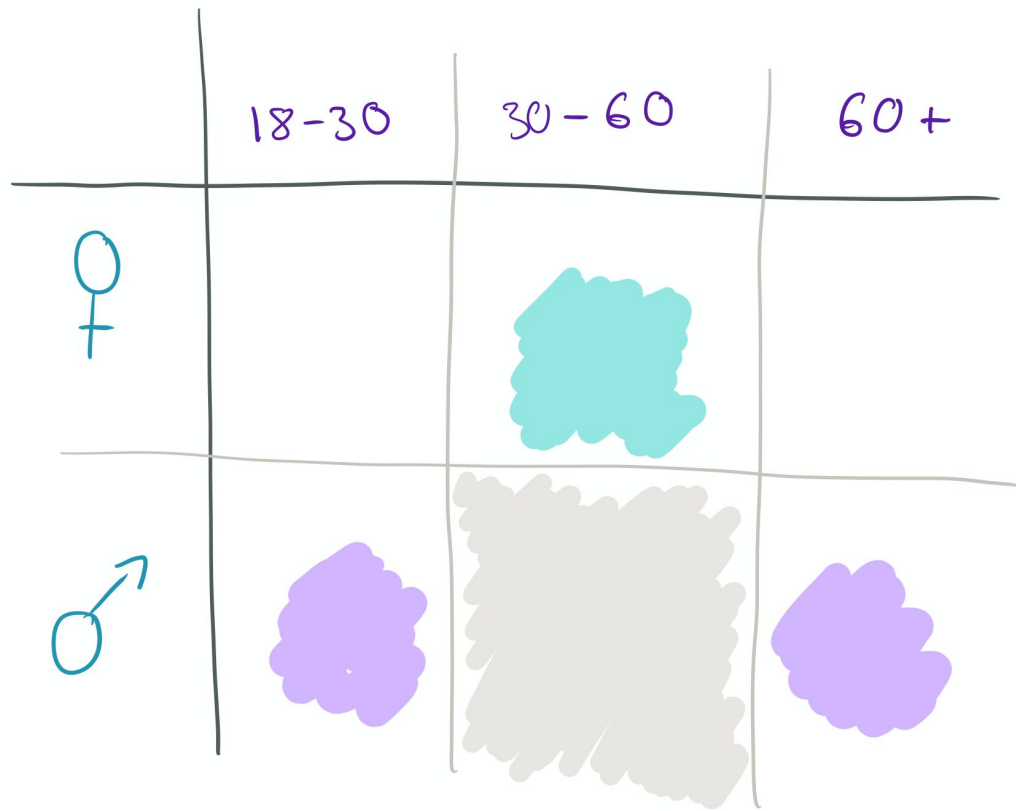
Multilevel Regression



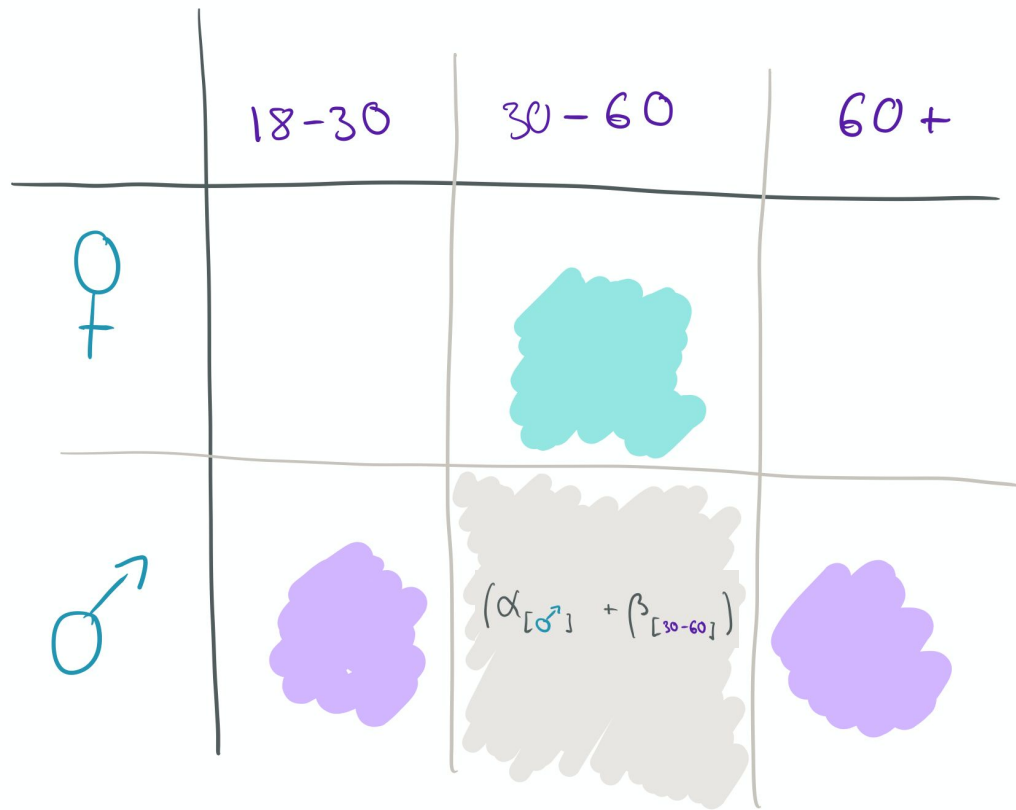
Multilevel Regression



Multilevel Regression



Multilevel Regression



Poststratification

Poststratification

	18-30	30-60	60+
♀	0.2	0.2	0.1
♂	0.1	0.3	0.1

Poststratification

$$\text{Total proportion of people that know brand} = 0.5 \times \text{Proportion of men that know brand} + 0.5 \times \text{Proportion of women that know brand}$$

Weight

Prediction
from our
Model

Poststratification

$$\begin{array}{l} \text{Total proportion} \\ \text{of people that} \\ \text{know brand} \end{array} = 0.5 \times \begin{array}{l} \text{Proportion} \\ \text{of men} \\ \text{that know} \\ \text{brand} \end{array} + 0.5 \times \begin{array}{l} \text{Proportion} \\ \text{of women} \\ \text{that know} \\ \text{brand} \end{array}$$

$P(\text{gender})$ \nearrow

$P(\text{knows brand} \mid \text{gender})$ \nearrow

Poststratification

$$\begin{pmatrix} 0.75 \\ 0.71 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ 0.68 \end{pmatrix} = 0.5 \times \begin{pmatrix} 0.63 \\ 0.68 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ 0.71 \end{pmatrix} + 0.5 \times \begin{pmatrix} 0.88 \\ 0.75 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ 0.64 \end{pmatrix}$$

On scale: Metaflow

What do you associate with this brand?



- ☒ Affordable
- ☐ Effective
- ☒ Fun
- ☐ Innovative
- ☐ User-friendly
- ☐ None of these

What do you associate with this brand?



One model per answer option

- ☒ Affordable
- ☐ Effective
- ☒ Fun
- ☐ Innovative
- ☐ User-friendly
- ☐ None of these

What do you associate with this brand?



- ☒ Affordable
- ☐ Effective
- ☒ Fun
- ☐ Innovative
- ☐ User-friendly
- ☐ None of these

One model per answer option

One question per brand, different competitor brands per market

~500 - 1500 models per project

What do you associate with this brand?



- ☒ Affordable
- ☐ Effective
- ☒ Fun
- ☐ Innovative
- ☐ User-friendly
- ☐ None of these

One model per answer option

One question per brand, different competitor brands per market

~500 - 1500 models per project

~20min per model

= ~10 days compute time



- Integrates with AWS Batch
- Easy to use for Data Scientists
- Supports reproducibility

MRP as Metaflow

```
from metaflow import FlowSpec, step

class MRPSFlow(FlowSpec):

    @step
    def start(self):
        Self.data, self.questions = load_data()
        self.next(self.run_model, foreach="questions")

    @step
    def run_model(self):
        question = self.input
        self.result = run_mrp(question, self.data)
        self.next

    @step
    def join(self, inputs):
        for result in inputs:
            save(result)

        self.next(self.end)

    @step
    def end(self):
        pass
```

MRP as Metaflow

```
from metaflow import FlowSpec, step

class MRFlow(FlowSpec):

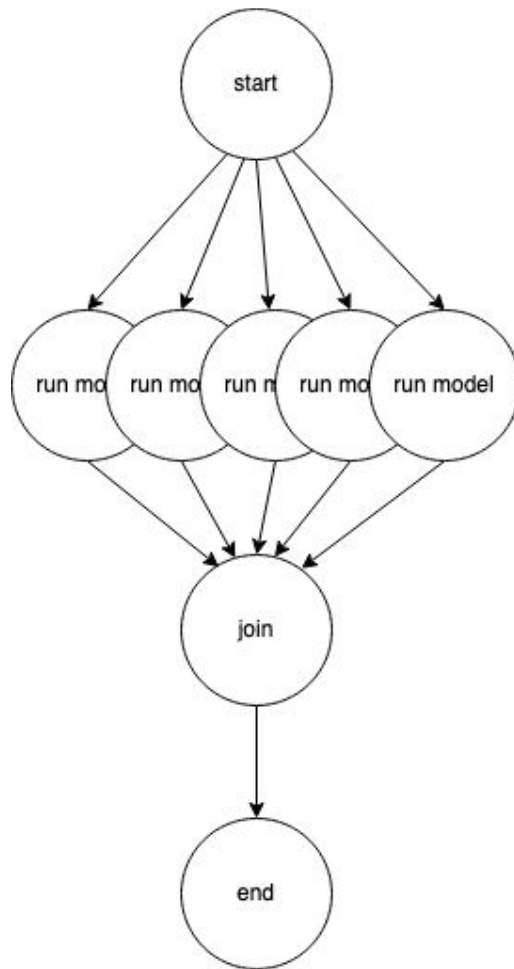
    @step
    def start(self):
        Self.data, self.questions = load_data()
        self.next(self.run_model, foreach="questions")

    @step
    def run_model(self):
        question = self.input
        self.result = run_mrp(question, self.data)
        self.next

    @step
    def join(self, inputs):
        for result in inputs:
            save(result)

        self.next(self.end)

    @step
    def end(self):
        pass
```



MRP as Metaflow

```
from metaflow import FlowSpec, step
```

```
class MRFlow(FlowSpec):
```

```
@step
```

```
def start(self):  
    Self.data, self.questions = load_data()  
    self.next(self.run_model, foreach="questions")
```

```
@step
```

```
def run_model(self):  
    question = self.input  
    self.result = run_mrp(question, self.data)  
    self.next
```

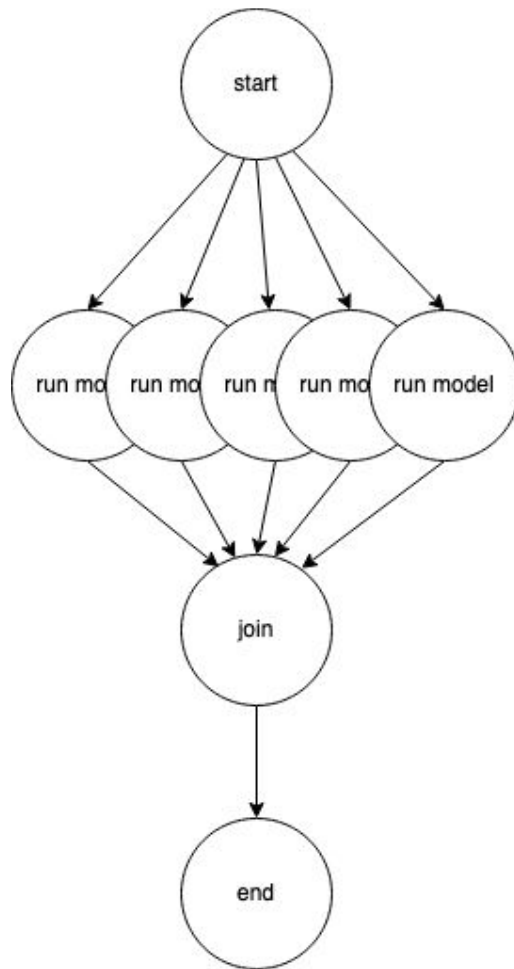
```
@step
```

```
def join(self, inputs):  
    for result in inputs:  
        save(result)
```

```
    self.next(self.end)
```

```
@step
```

```
def end(self):  
    pass
```



Parallelizing models

```
@step
def start(self):
    Self.data, self.questions = load_data()
    self.next(self.run_model, foreach="questions")
```

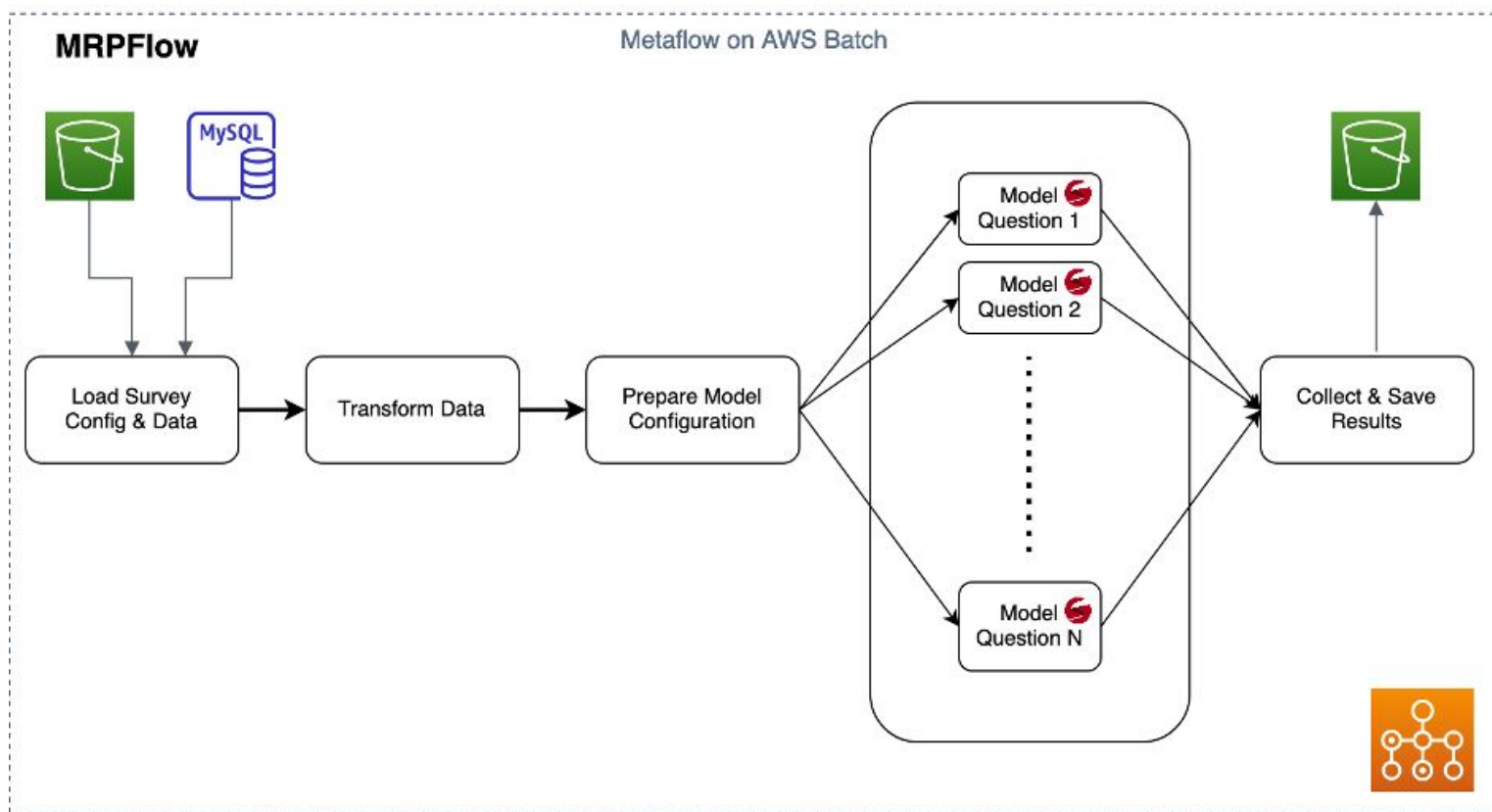
```
@step
def run_model(self):
    question = self.input
    self.result = run_mrp(question, self.data)
    self.next
```

Increasing resources

```
@step
def start(self):
    Self.data, self.questions = load_data()
    self.next(self.run_model, foreach="questions")

@resources(cpu=8, memory=32000)
@step
def run_model(self):
    question = self.input
    self.result = run_mrp(question, self.data)
    self.next
```

Mr.P on AWS



Challenges



Convergence

How to monitor convergence of 1000+ models?



More predictor variables

Full joint distribution needed of all predictor variables.

Summary

- Multilevel-regression improves errors by using grouped structure
- Propagation of uncertainty improves weighting

Corrie Bartelheimer
Senior Data Scientist
corrie.bartelheimer@latana.com

Resources and Links

Introductory book on Bayesian Statistics: <https://xcelab.net/rm/statistical-rethinking/>

Stan: <https://mc-stan.org/>

Stan interface brms (R): <https://paul-buerkner.github.io/brms/>

MRP: Forecasting elections with non-representative polls <https://www.sciencedirect.com/science/article/abs/pii/S0169207014000879>

Metaflow <https://metaflow.org/>

MRP at Latana:

- <https://latana.com/whitepapers/mrp-vs-traditional-quota-sampling-brand-tracking/>
- <https://aws.amazon.com/blogs/startups/brand-tracking-with-bayesian-statistics-and-aws-batch/>