



# Automating Inventory at Stitch Fix

Using Beta Binomial Regression for Cold Start Problems

Sally Langford - Data Scientist

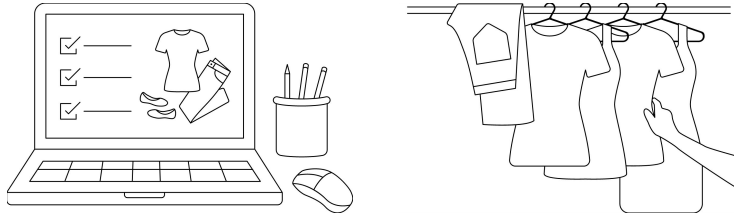
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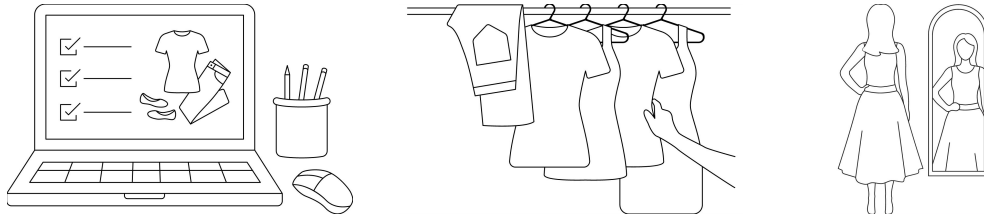
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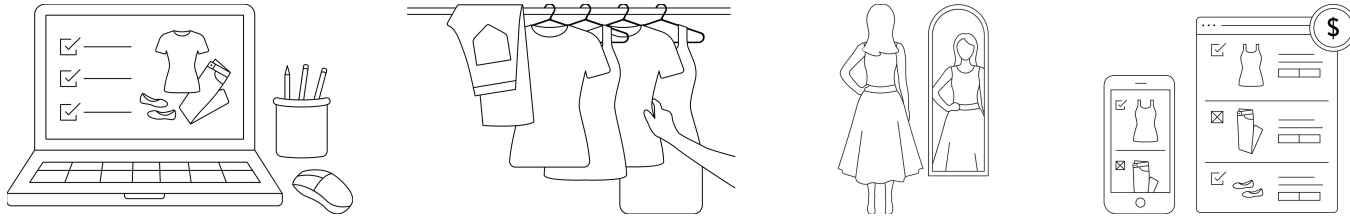
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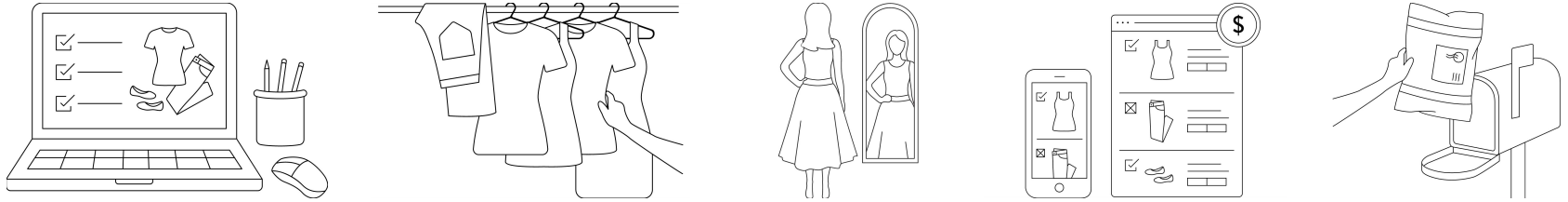
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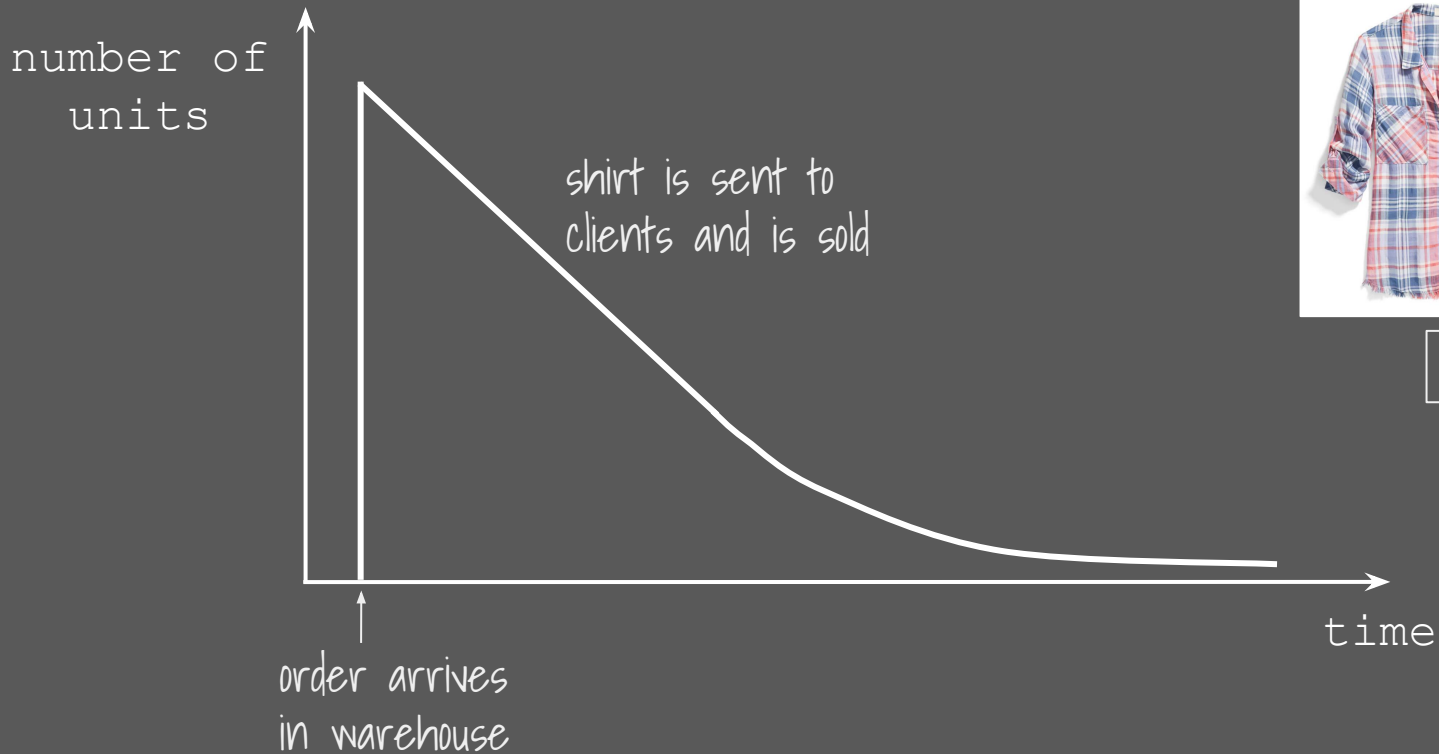
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- A personal stylist will curate five pieces for you.
- Try all the items on at home.
- Give your stylist feedback on all items, then only pay for what you keep.
- Return the other items in envelope provided.

## Benefits of Machine Learning in Inventory Management:

- Scalable with business.
- Rapid reforecasting.
- Capture nonlinear relationships.
- Cold start problems.

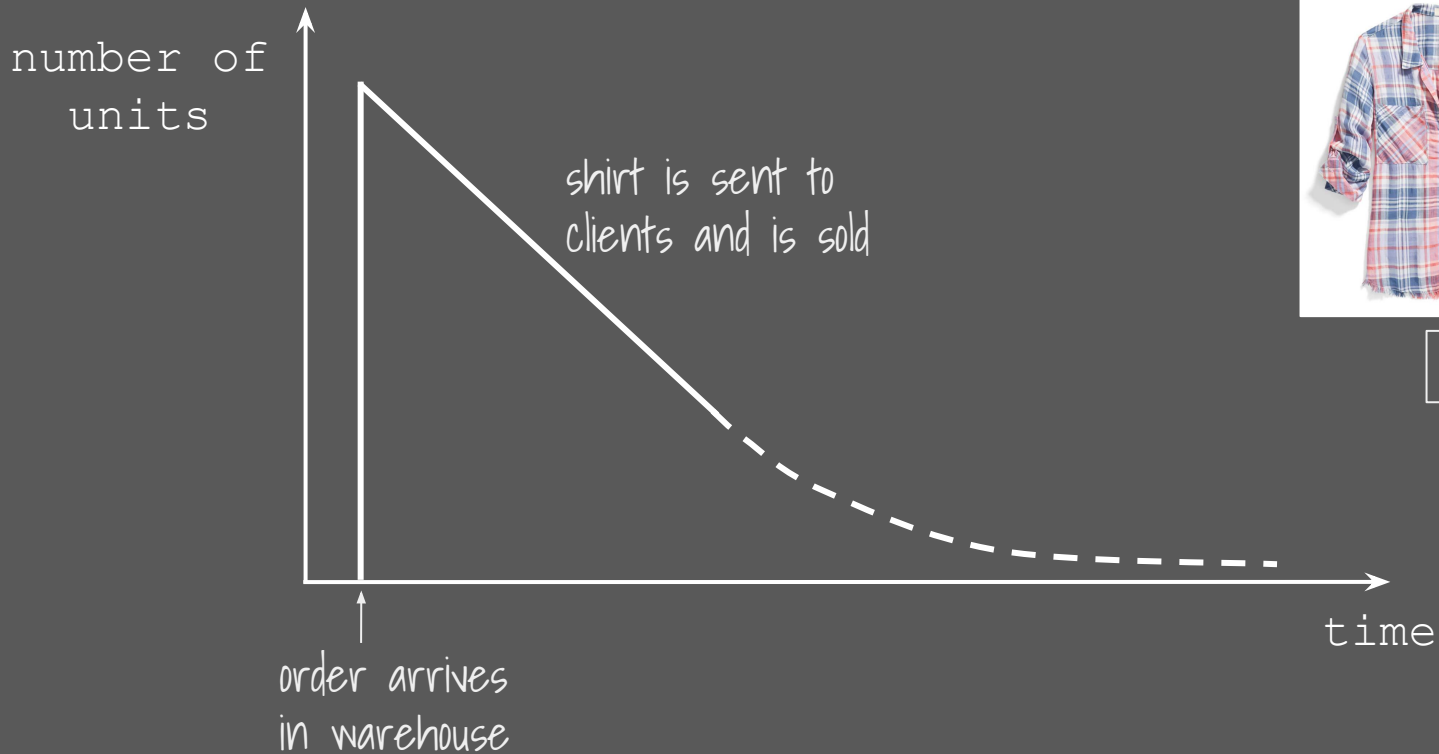






plaid shirt





plaid shirt

Inventory consumption of a style is proportional to;

- daily demand,
- clients for which the style is recommended,
- whether there are units in the warehouse,
- probability a stylist chooses to send the client this style,
- if the client buys the style.

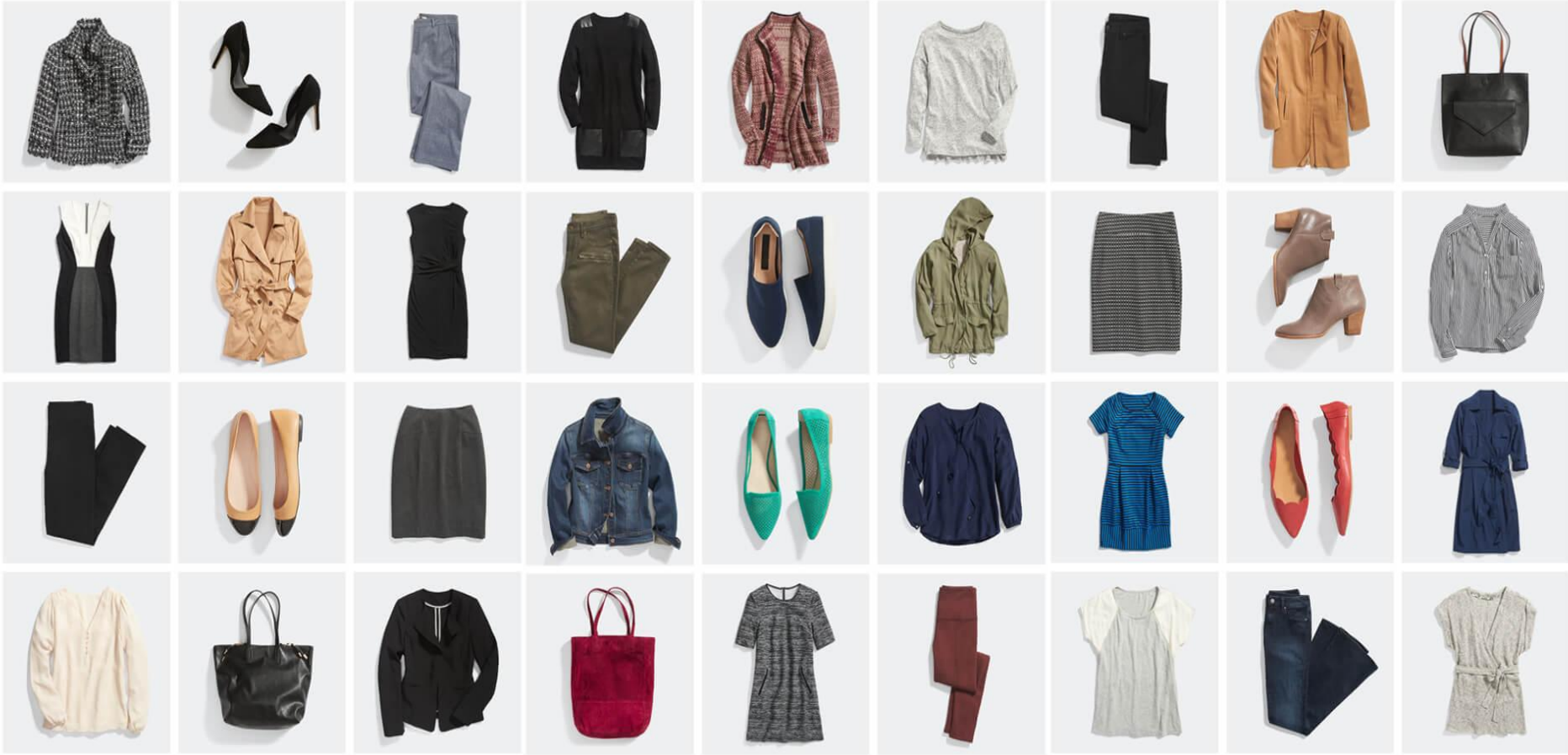
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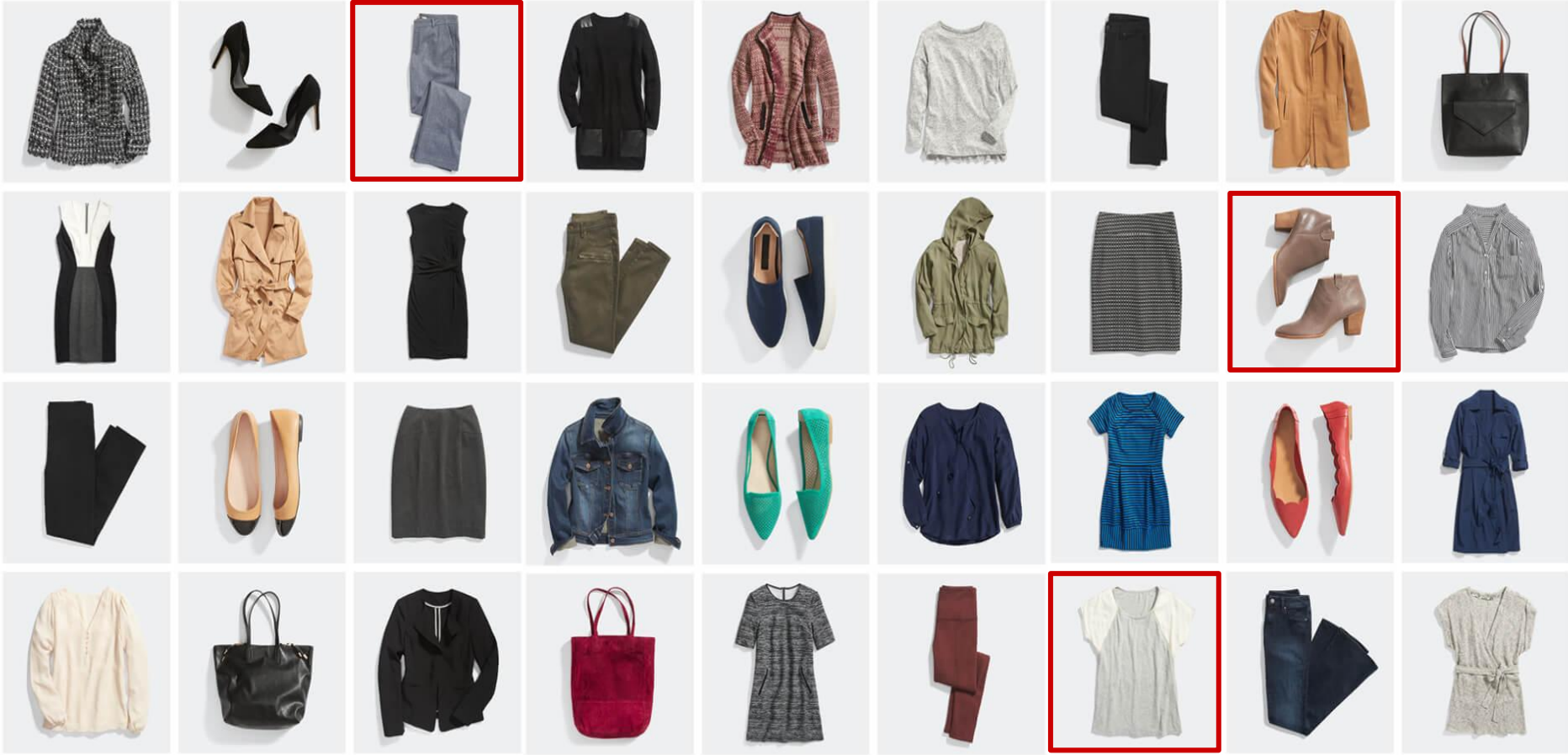
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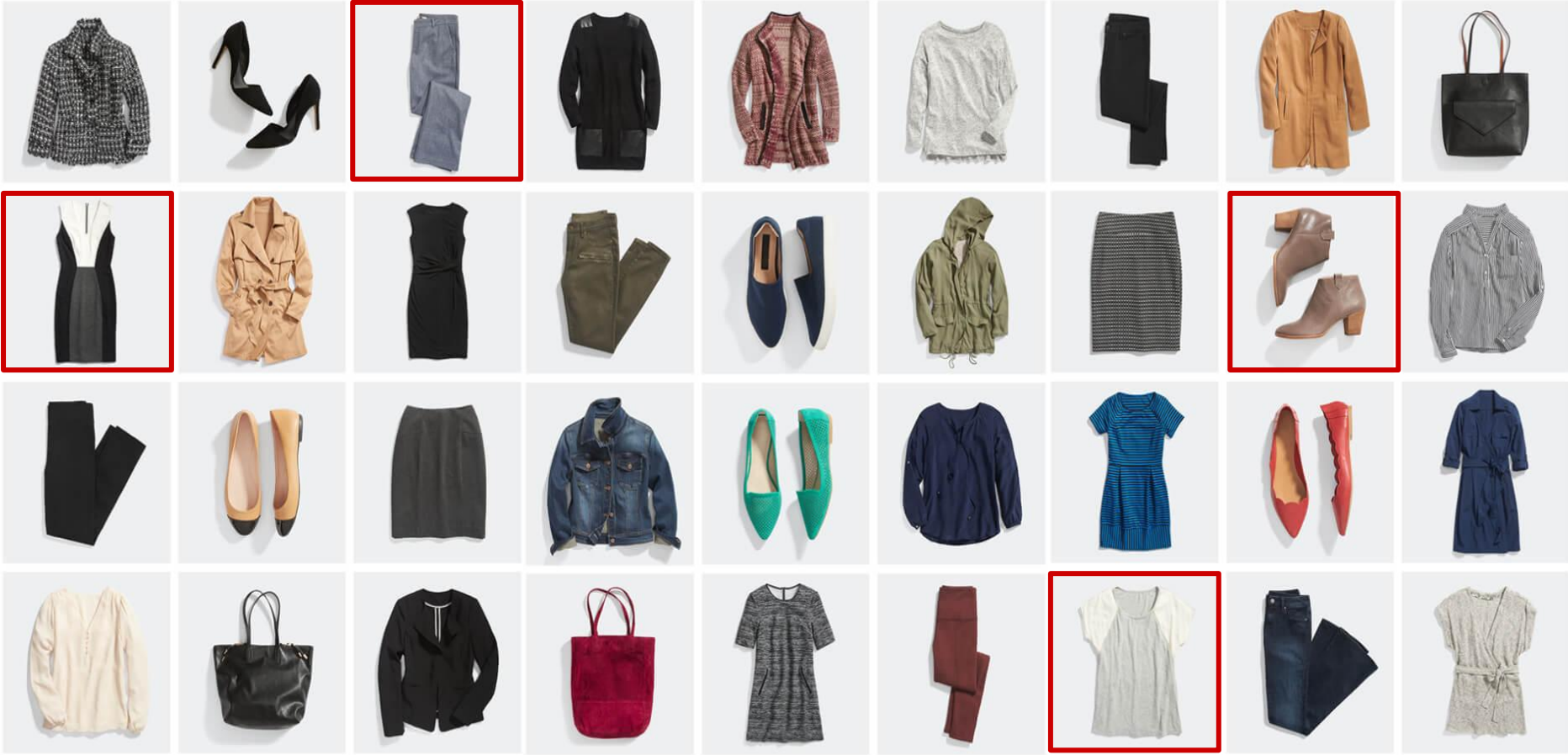
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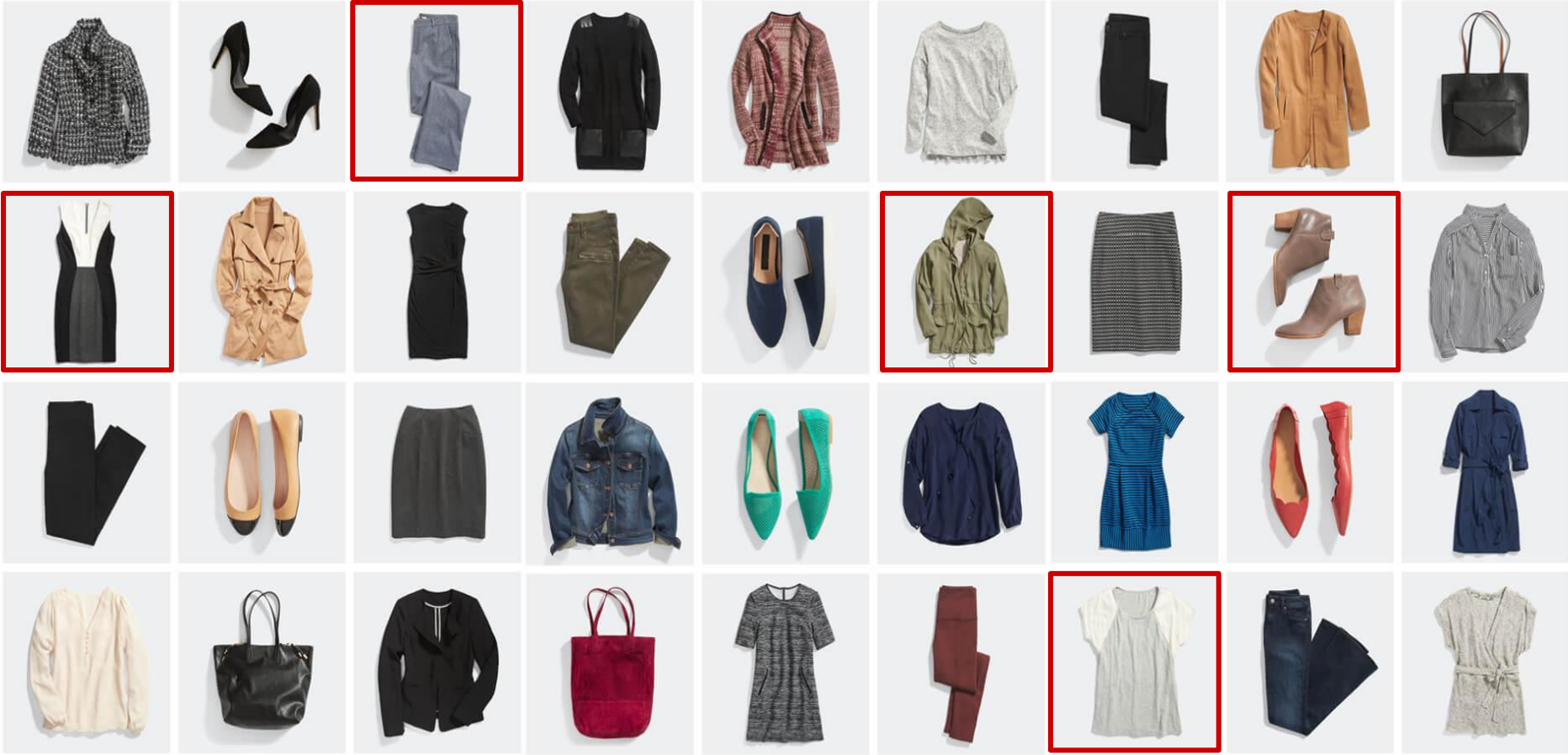


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plaid long-sleeve shirt



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plaid long-sleeve shirt





plaid long-sleeve shirt





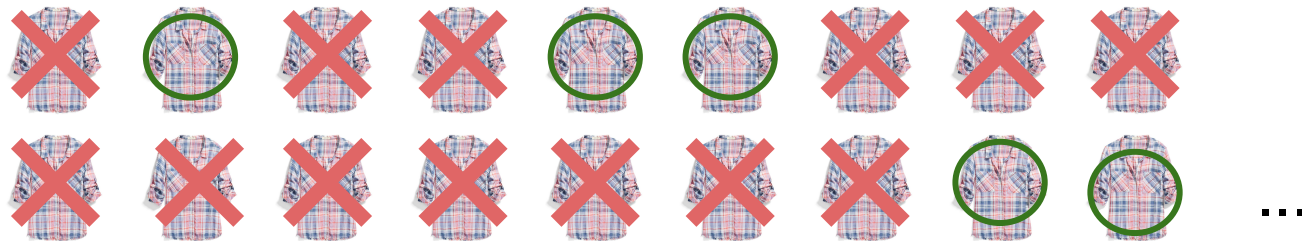
plaid long-sleeve shirt



...



plaid long-sleeve shirt

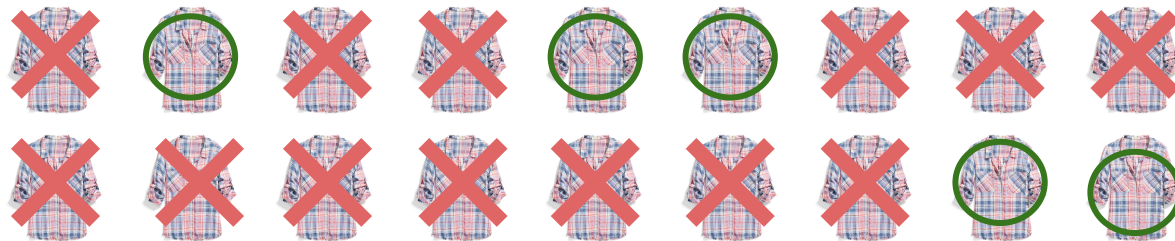


$$P(\text{chosen}) + P(\text{not chosen}) = 1$$





plaid long-sleeve shirt

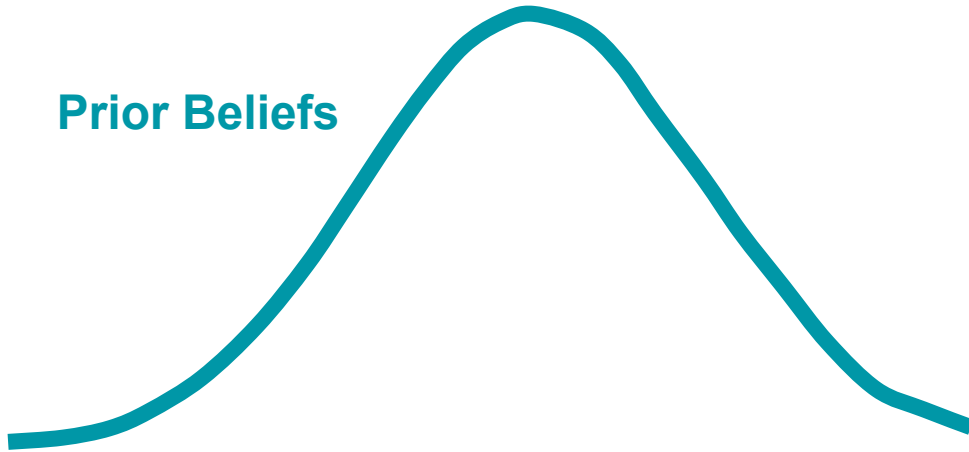


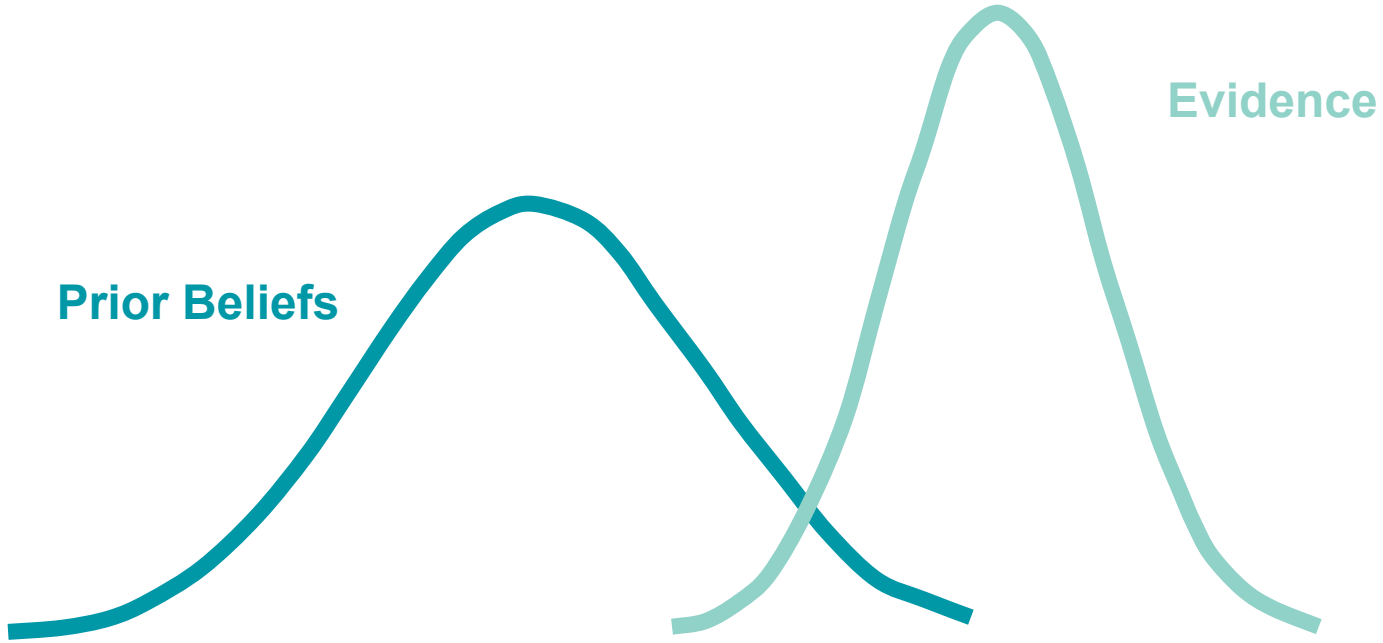
blue long-sleeve shirt

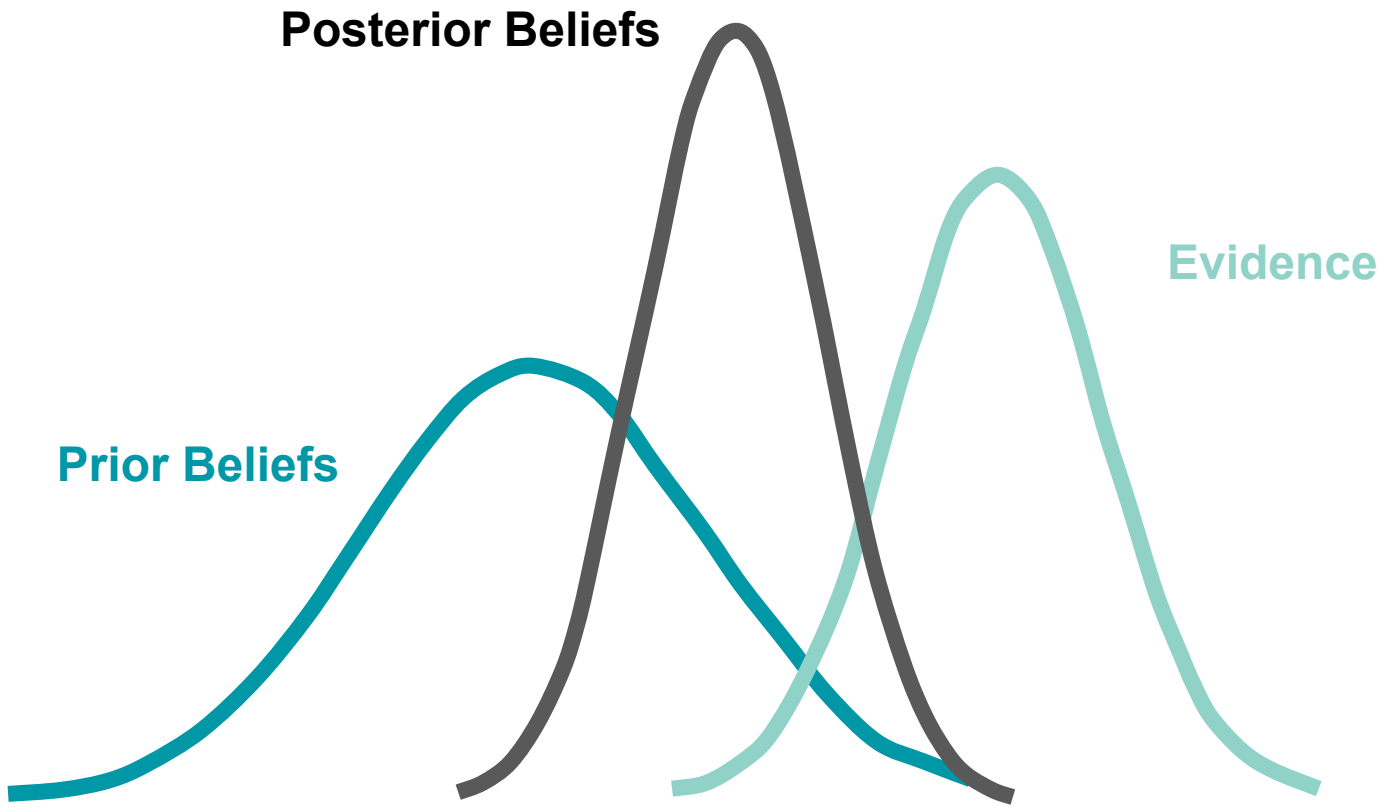




**Prior Beliefs**







$$N \sim \text{Binom}(N_{av}, p)$$



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$$p \sim B(\alpha, \beta)$$

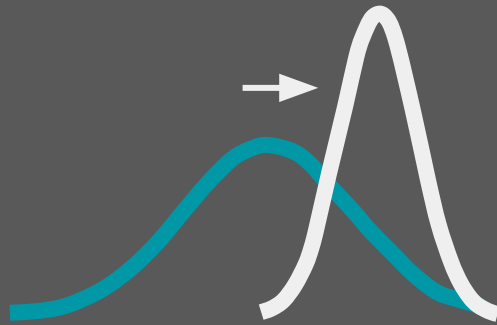




$$B(\alpha', \beta') = B(\alpha_0 + k, \beta_0 + n - k)$$



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**Step 1:** Use maximum likelihood to calculate  $\alpha_0$  and  $\beta_0$  for the distribution of  $\mathbf{p}$  in groups of similar styles.

**Step 2:** After a period of time, update this prior for the number of times the new style has been recommended for a client ( $\mathbf{n}$ ), and chosen to be sent ( $\mathbf{k}$ ).

**Step 3:** Calculate the mean and confidence interval of  $\mathbf{p}$  from the resulting distribution. This is used as the probability that the new style will be chosen to be sent to a client.

**Step 4:** Repeat steps 2-3.



VGAM (in python):

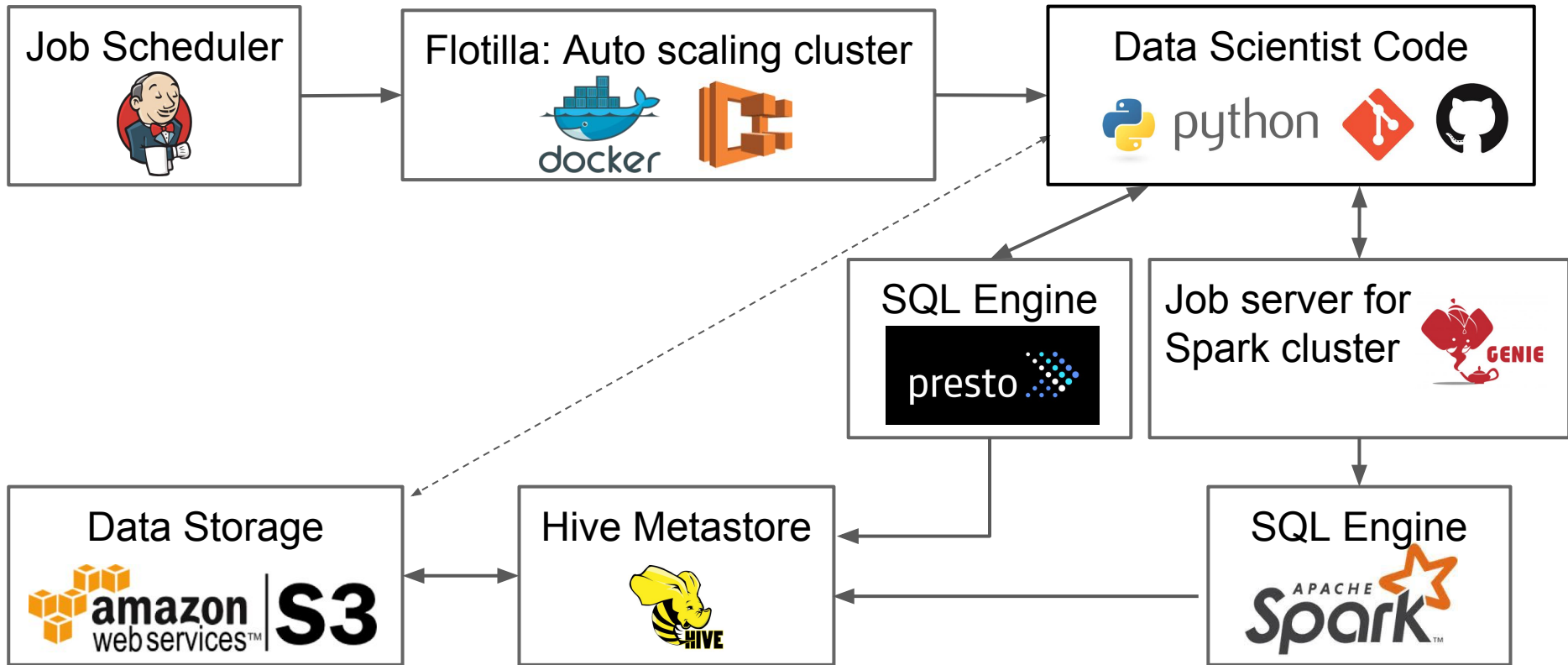
```
import rpy2.objects as objects
objects.r.library("VGAM")
objects.r("fit = vglm(cbind(successData,trialData - successData) ~ 1,
                    betabinomialff, trace=TRUE)")
alpha, beta = objects.r("Coef(fit)")
```

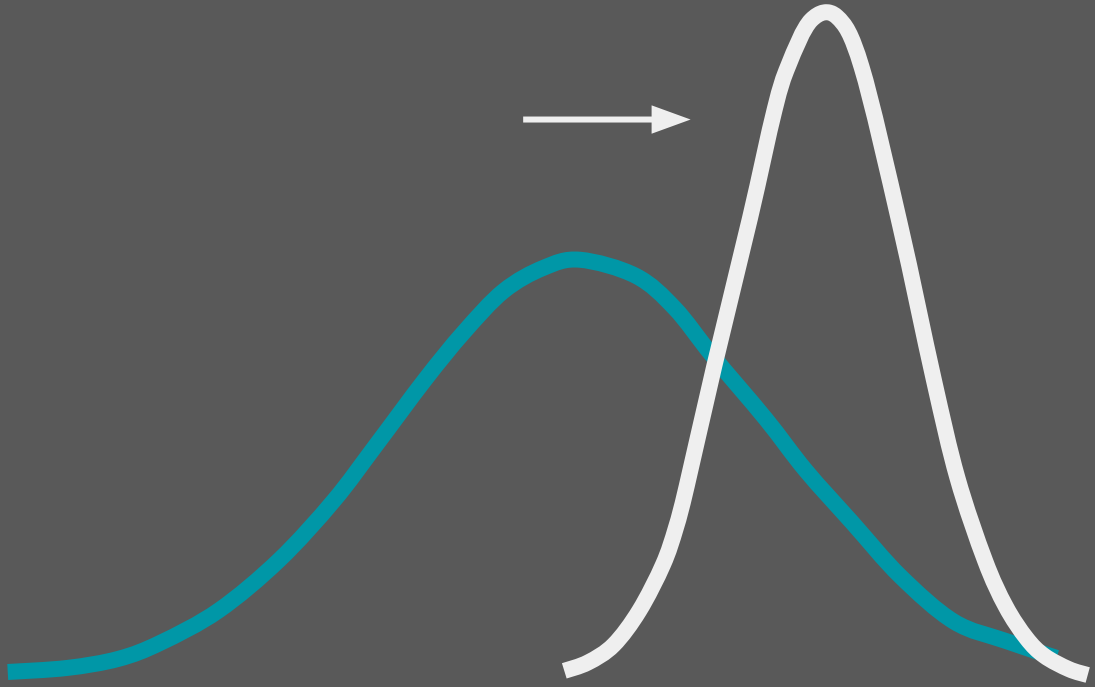


```
import scipy
fit = scipy.stats.beta.fit(data, floc=0, fscale=1)
alpha, beta = fit[0], fit[1]

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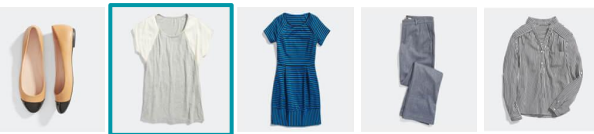
result = scipy.optimize.minimize(loss_function, p0, jac=True, **kwargs)
```



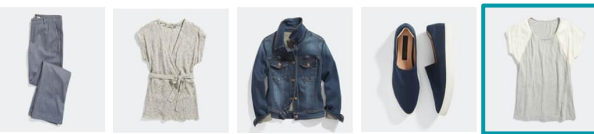




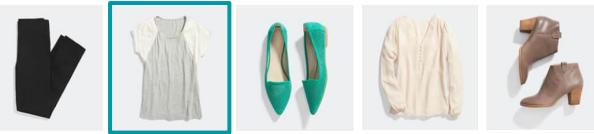
Top 5 recommendations for client A



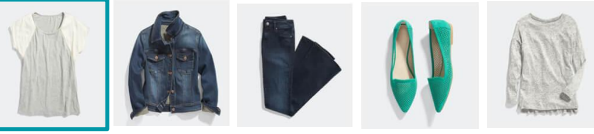
Top 5 recommendations for client B



Top 5 recommendations for client C

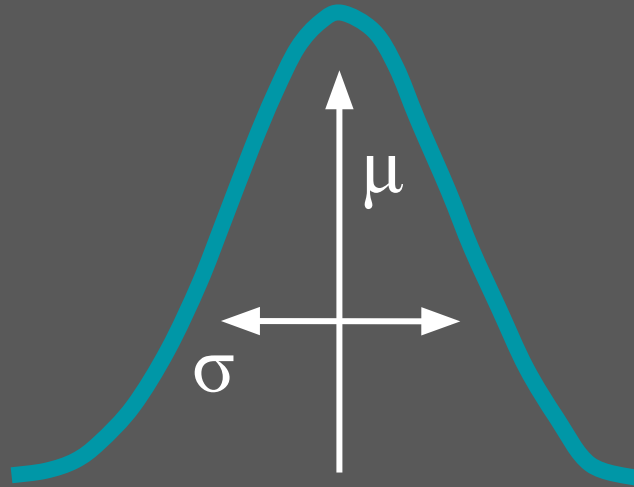


Top 5 recommendations for client D



Top 5 recommendations for client E

$$B(\alpha, \beta) = B(\mu/\sigma, (1 - \mu)/\sigma)$$





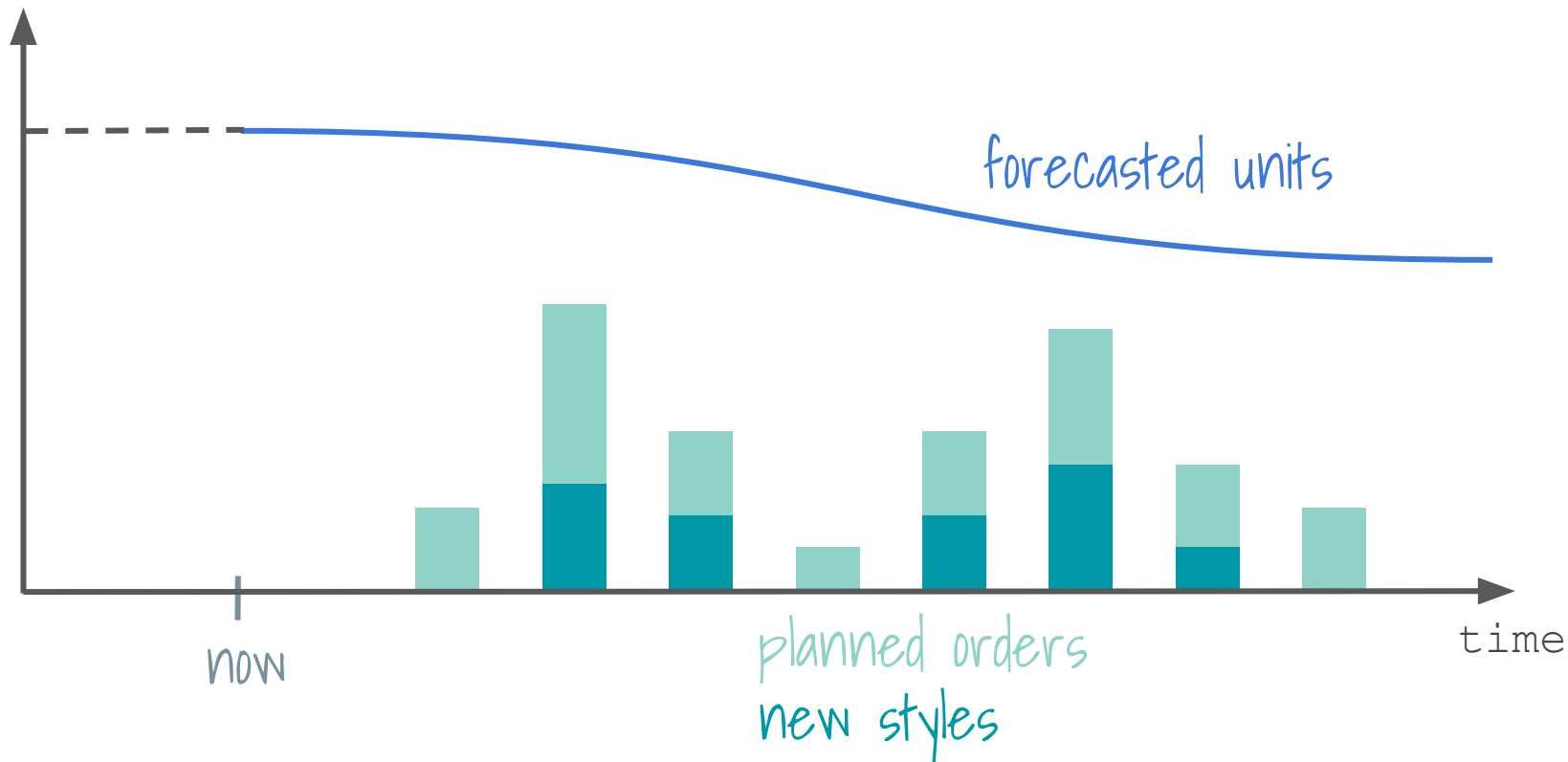
$$\mu = \mu_0 + \mu_n \log(1 + n)$$



number of  
units



number of  
units



## How do we use our inventory forecast model?

- When should we re-order inventory?
- How should we buy inventory by size?
- How should orders be separated into different warehouses?
- When should a style not be sent out anymore, in place of a new option?

## Metrics of success:

- Fraction of inventory out with clients compared to in the warehouse?
- How many styles are available to send to a client?
- $\Delta$  in the beginning of month projected units.
- Cumulative units sold over time.

Do you want to calculate the probability of success in a binomial process?

Not enough data?

Use Beta Binomial Regression for your cold start problem!



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