

Cohere Research Talk: Massively Parallel Inference & Bayesian Evals

Sam Bowyer

10 November 2025

Outline

- 1 About Me
- 2 Alan: Massively Parallel Probabilistic Programming
- 3 Bayesian Evals: Uncertainty Quantification for LLM Evals

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- Currently working on discrete diffusion models (training an 'auxilliary' model with VI to suggest the order in which to decode tokens).
- Two projects I'll be talking about today: Alan (massively parallel probabilistic programming) & Bayesian Evals.

Alan: A Massively Parallel Probabilistic Programming Language



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 - Develop ‘massively parallel’ Bayesian inference algorithms: fast, accurate, and scalable; desinged for GPU acceleration.

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- Dual goals:
 - Develop ‘massively parallel’ Bayesian inference algorithms: fast, accurate, and scalable; designed for GPU acceleration.
 - Implement these algorithms in a probabilistic programming language in pytorch (`alan`), allowing users to specify general probabilistic models.

Regular Bayesian Inference

- **Bayesian inference:** Prior $P(z)$ and likelihood $P(x|z)$ for latent variables z and data x .

$$P(z|x) = \frac{P(x|z)P(z)}{\int_{\mathcal{Z}} P(x, z') dz'}$$

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- 3 Approximate the normalising constant using the 'global' estimator:

$$\mathcal{P}_{\text{global}}(z) = \frac{1}{K} \sum_{k=1}^K r_k(z) \quad \text{such that} \quad \mathbb{E}_{z \sim Q}[\mathcal{P}_{\text{global}}(z)] = P(x).$$

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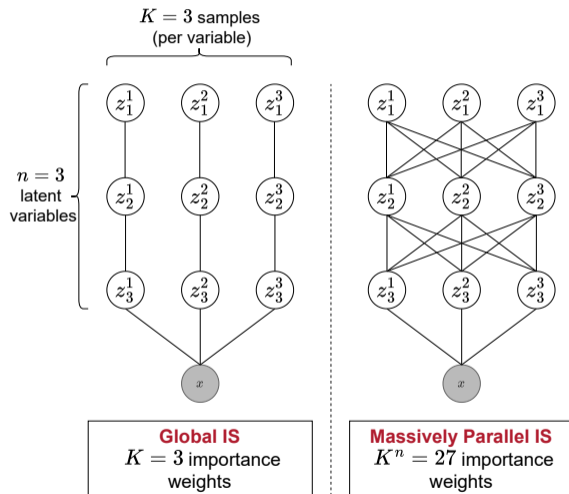
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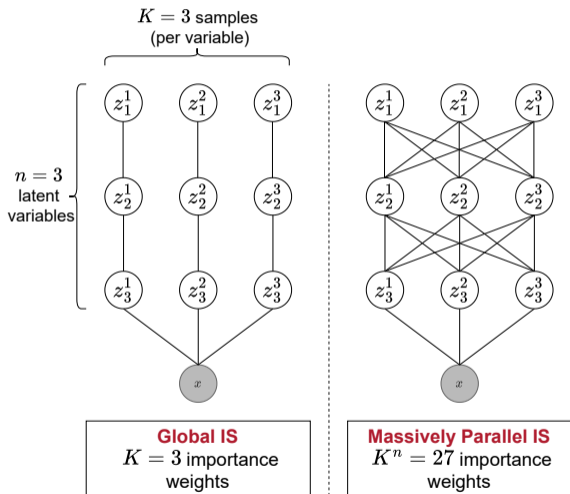
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- Solution: **Massively Parallel Importance Sampling (MP-IS)**
 - Reason about all K^n possible joint samples at once.

Massively Parallel Importance Sampling (MP-IS)



- Suppose each latent sample $z^k = (z_1^k, \dots, z_n^k) \sim Q(z)$ is comprised of n variables.

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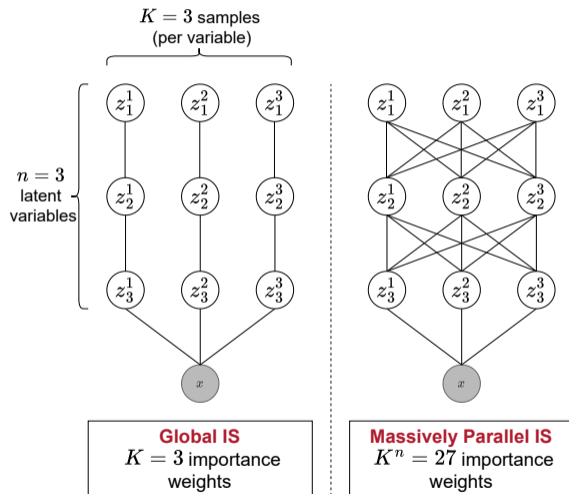


- Suppose each latent sample $z^k = (z_1^k, \dots, z_n^k) \sim Q(z)$ is comprised of n variables.
- We can construct K^n different samples from the full joint space

$$(z_1^{k_1}, \dots, z_n^{k_n}) \in \mathcal{Z}$$

where $\mathbf{k} = (k_1, \dots, k_n) \in [K]^n$ is the indexing vector for each latent variable.

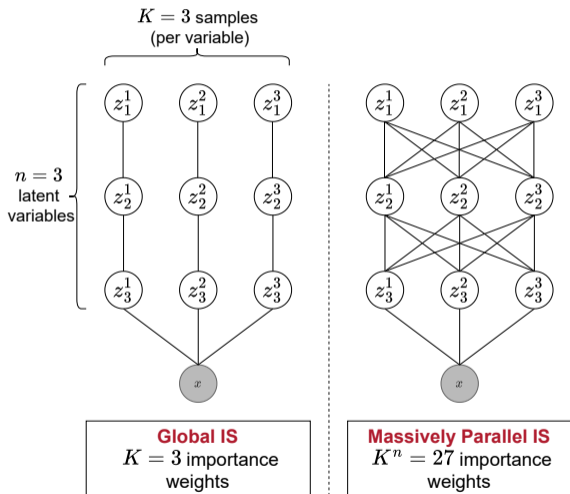
Massively Parallel Importance Sampling (MP-IS)



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- Rather than using the global IS estimator

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- ...we can use the MP-IS estimator

$$\mathcal{P}_{\text{MP}}(z) = \frac{1}{K^n} \sum_{\mathbf{k} \in [K]^n} \frac{P(x, \mathbf{z}^{\mathbf{k}})}{Q_{\text{MP}}(\mathbf{z}^{\mathbf{k}}, \mathbf{k})}.$$

(Which is still unbiased.)

MP-IS: Some Complications...

$$\mathcal{P}_{\text{MP}}(z) = \frac{1}{K^n} \sum_{\mathbf{k} \in [K]^n} \frac{P(x, z^{\mathbf{k}})}{Q_{\text{MP}}(z^{\mathbf{k}}, \mathbf{k})} = \frac{1}{K^n} \sum_{\mathbf{k} \in [K]^n} r_{\mathbf{k}}(z).$$

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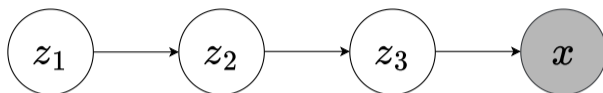
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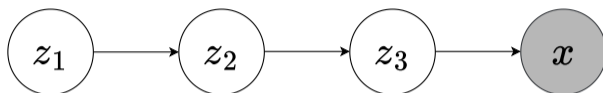
- We have to be careful about how we define Q_{MP} over the space of all K^n joint samples.
- Also, at first glance, this thing doesn't look all that nice to compute...
- But we can exploit the conditional independencies in the model to render it tractable.

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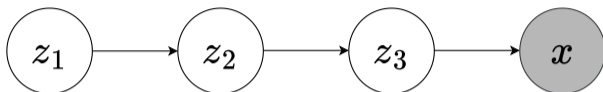
- E.g. with the model from before with $n = 3$, $P(x, z) = P(z_1)P(z_2|z_1)P(z_3|z_2)P(x|z_3)$, we can move the sums inside the product and get a bunch of tensor products:

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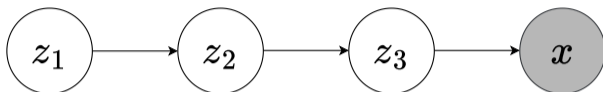
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$$\begin{aligned}\mathcal{P}_{\text{MP}}(z) &= \frac{1}{K^3} \sum_{k_1 \in [K]} \sum_{k_2 \in [K]} \sum_{k_3 \in [K]} \frac{P(z_1^{k_1})P(z_2^{k_2}|z_1^{k_1})P(z_3^{k_3}|z_2^{k_2})P(x|z_3^{k_3})}{Q(z_1^{k_1})Q(z_2^{k_2})Q(z_3^{k_3})} \\ &= \frac{1}{K^3} \sum_{k_1 \in [K]} \underbrace{\frac{P(z_1^{k_1})}{Q(z_1^{k_1})}}_{\text{Vector of size } K} \sum_{k_2 \in [K]} \underbrace{\frac{P(z_2^{k_2}|z_1^{k_1})}{Q(z_2^{k_2})}}_{\text{Matrix of size } K \times K} \sum_{k_3 \in [K]} \underbrace{\frac{P(z_3^{k_3}|z_2^{k_2})}{Q(z_3^{k_3})}}_{\text{Matrix of size } K \times K} \underbrace{P(x|z_3^{k_3})}_{\text{Vector of size } K}\end{aligned}$$

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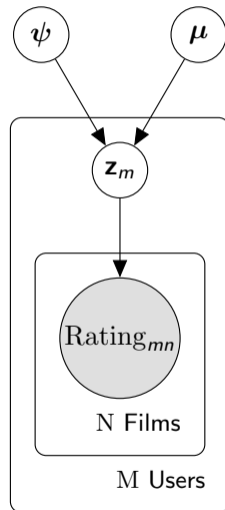
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Can we hide these complications from the user?

- Yes! We do this with `alan`.
- User specifies the model with `P` and `Q` as pytorch modules, and we handle the massively parallel inference for them.

Alan: A Probabilistic Programming Language

```
1 from alan import Normal, Bernoulli, Plate, BoundPlate, OptParam, Data, Problem
2 import torch as t
3
4 # Set up the model
5 d_z = 10
6
7 P = Plate(
8     mu_z = Normal(t.zeros((d_z,)), t.ones((d_z,))),
9     psi_z = Normal(t.zeros((d_z,)), t.ones((d_z,))),
10    plate_1 = Plate(
11        z = Normal("mu_z", lambda psi_z: psi_z.exp()),
12        plate_2 = Plate(
13            obs = Bernoulli(logits = lambda z, x: z @ x),
14        )
15    ),
16)
17
18 Q = Plate(
19    mu_z = Normal(OptParam(t.zeros((d_z,))), OptParam(t.zeros((d_z,)), transformation=t.exp)),
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24            obs = Data()
25        )
26    ),
27)
28
29 P = BoundPlate(P, platesizes={'plate_1': num_users, 'plate_2': num_movies}, inputs = {'x': x})
30 Q = BoundPlate(Q, platesizes={'plate_1': num_users, 'plate_2': num_movies}, inputs = {'x': x})
31
32 prob = Problem(P, Q)
```



- Using $\mathcal{P}_{\text{MP}}(z)$, we can do variational inference (VI) by maximising the ELBO:

$$\log P(x) \geq \mathcal{L}_{\text{MP}}(\theta) = \mathbb{E}_{z \sim Q_{\text{MP}}(\theta)}[\log \mathcal{P}_{\text{MP}}(z)]$$

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- Aitchison (2019) showed that MP-VI is a tighter bound than the global VI objective (IWAE):

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31
32 prob = Problem(P, Q)
33 opt = t.optim.Adam(prob.Q.parameters(), lr=lr)
34
35 # Train Q with VI
36 for i in range(num_iterations):
37     opt.zero_grad()
38     elbo = prob.sample(K=K).elbo_vi()
39     elbo.backward()
40     opt.step()

```

MP Algorithms

- We can obtain unbiased posterior moment estimates via autodiff (Bowyer et al. (2024)).

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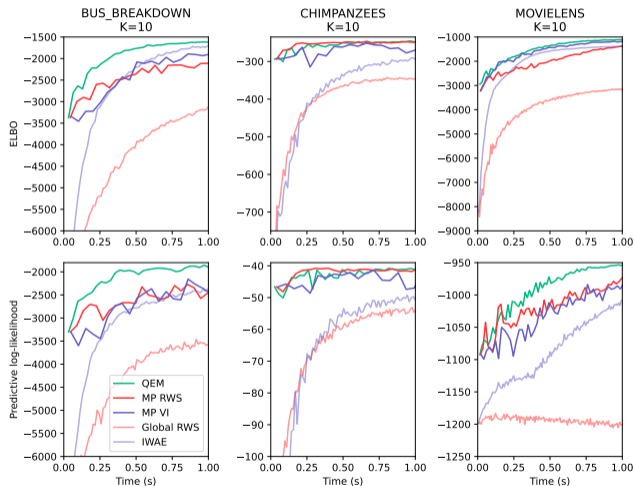
- By similar arguments: $J \in \mathbb{R}^K$ gives us marginal importance weights; $J \in \mathbb{R}^{K^{1+|pa(i)|}}$ gives us importance samples for z_i , given its parents $pa(i)$.

QEM: An Adaptive Importance Sampling Algorithm

QEM (Heap et al. (2025))

- 1 Start with an initial approximate posterior Q_0 .
- 2 Compute posterior moment estimates $m_{\text{MP}}(z)$ using MP-IS.
- 3 Update the approximate posterior Q_{t+1} using the moment estimates.

Can be seen as an EM-like algorithm for adaptive importance sampling.



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- This project was a great (if, at times, complicated) way to learn about Bayesian inference and numerical and probabilistic programming.
- The results were pretty promising, but but there are some drawbacks to massively parallel methods:
 - The algorithms are complex to implement (hence wrapping them in a PPL).
 - Not all models have lots of conditional independencies to exploit.
 - Although it's slower and harder to tune, HMC is often hard to beat in terms of quality of inference.

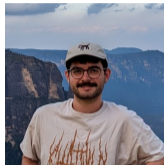
Bayesian Evals: Uncertainty Quantification for LLM Evals



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- The former direction led to an ICML spotlight position paper: *'Position: Don't Use the CLT in LLM Evals With Fewer Than a Few Hundred Datapoints'*.

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- The former direction led to an ICML spotlight position paper: *'Position: Don't Use the CLT in LLM Evals With Fewer Than a Few Hundred Datapoints'*.
- The latter fell by the wayside, but is something I'd like to come back to at some point.

Central Limit Theorem (CLT)

If X_1, \dots, X_N are IID r.v.s with mean $\mu \in \mathbb{R}$ and finite variance σ^2 , then

$$\sqrt{N}(\hat{\mu} - \mu) \xrightarrow{d} \mathcal{N}(0, \sigma^2) \text{ as } N \rightarrow \infty,$$

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- The CLT-based confidence interval is:

$$\text{CI}_{1-\alpha}(\mu) = \hat{\mu} \pm z_{\alpha/2} \text{SE}(\hat{\mu})$$

where $z_{\alpha/2}$ is the $100(1 - \alpha/2)$ -th percentile of $\mathcal{N}(0, 1)$ and $\text{SE}(\hat{\mu}) = \sqrt{\frac{\hat{\sigma}^2}{N}}$ is the standard error of the sample mean.

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$$\text{CI}_{1-\alpha}(\mu) = \hat{\mu} \pm z_{\alpha/2} \text{SE}(\hat{\mu})$$

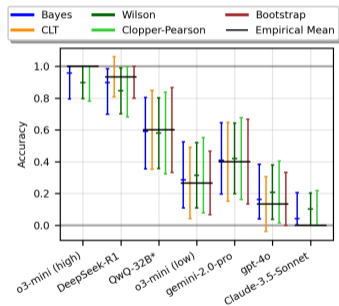
where $z_{\alpha/2}$ is the $100(1 - \alpha/2)$ -th percentile of $\mathcal{N}(0, 1)$ and $\text{SE}(\hat{\mu}) = \sqrt{\frac{\hat{\sigma}^2}{N}}$ is the standard error of the sample mean.

- In the case of binary data $X_i \in \{0, 1\}$, this becomes:

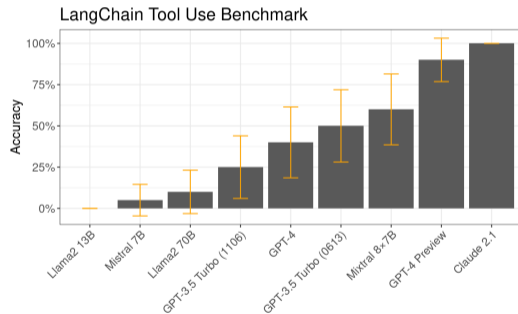
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Real-World Failures of the CLT

- If N is too small, CLT-based error bars can collapse to **zero-width** or **extend past $[0, 1]$** .



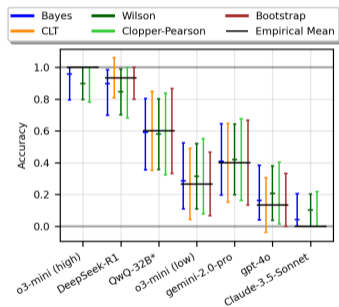
Math Arena's AIME II 2025 Benchmark (N=15). Various 95% interval types shown.



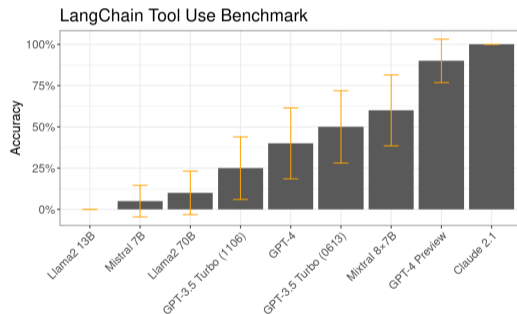
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Real-World Failures of the CLT

- If N is too small, CLT-based error bars can collapse to **zero-width** or **extend past $[0, 1]$** .
- Smaller, more intricate, and expensive LLM benchmarks are becoming increasingly common, so we need to find alternatives for the few-data regime.



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Bayesian Alternative: Beta-Binomial Model

- Treat the data as IID Bernoulli with a **uniform prior** on the parameter θ .

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$$p(\theta|y_{1:N}) = \text{Beta} \left(1 + \sum_{i=1}^N y_i, 1 + \sum_{i=1}^N (1 - y_i) \right)$$

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Beta-Bernoulli Bayesian Credible Interval

```
1 posterior = scipy.stats.beta(1 + sum(y), 1 + N - sum(y))  
2 bayes_ci  = posterior.interval(confidence=0.95)
```

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Wilson & Clopper-Pearson Confidence Interval

```
1 result = scipy.stats.binomtest(k=sum(y), n=N)
2 wilson_ci = result.proportion_ci("wilson", 0.95)
3 clop_ci    = result.proportion_ci("exact", 0.95)
```

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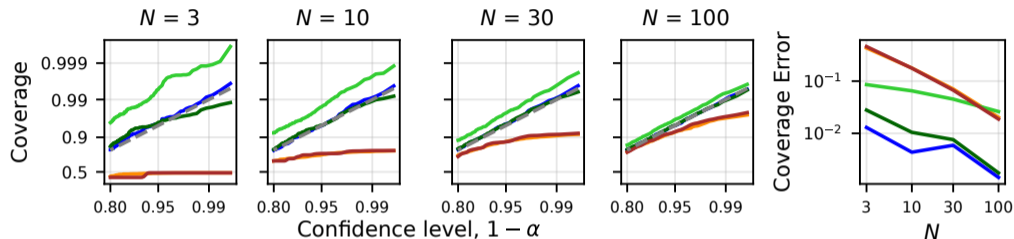
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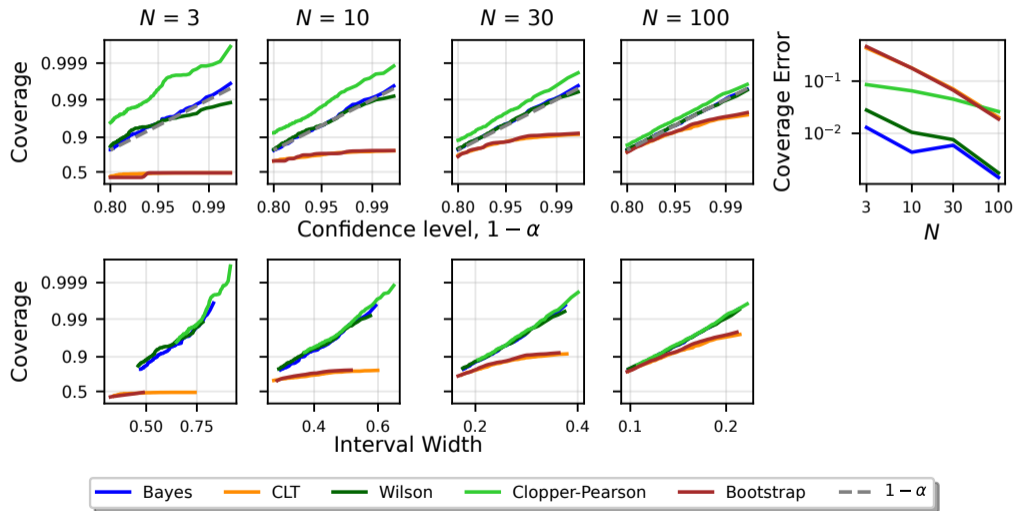
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 - Ideally, coverage = $1 - \alpha$.

IID Questions Setting: Results



Bayes CLT Wilson Clopper-Pearson Bootstrap $1 - \alpha$

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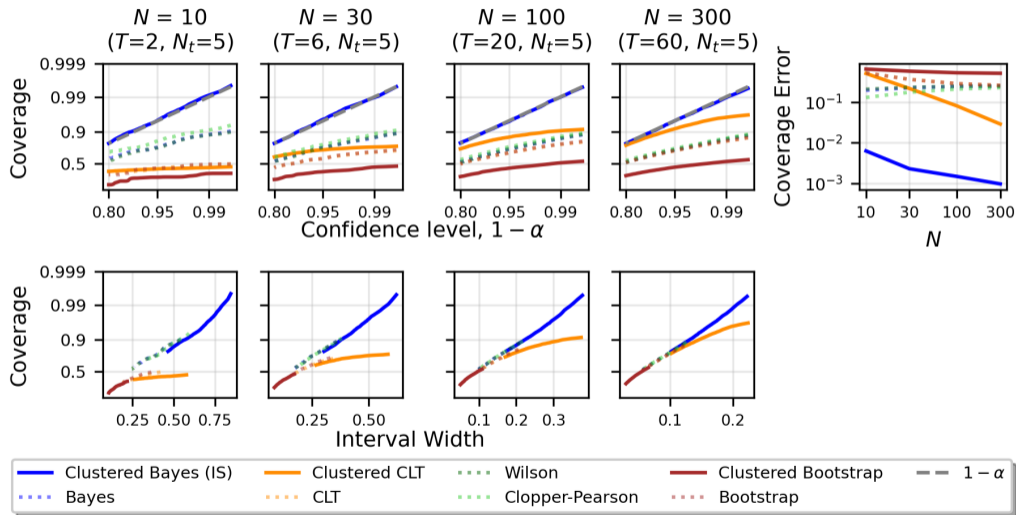
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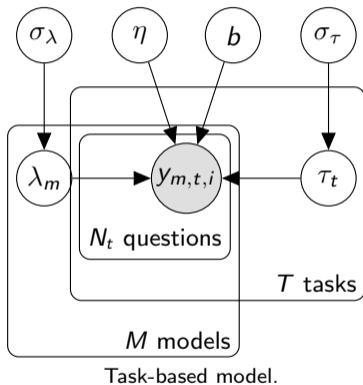
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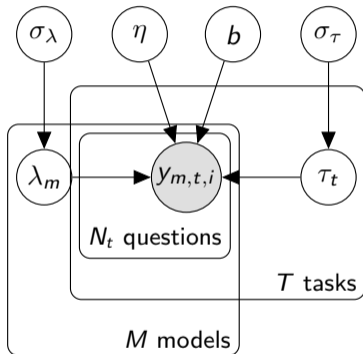
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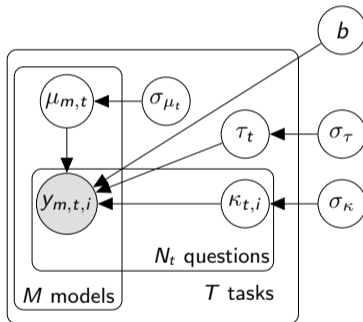


Bayesian Evals for Interpretability

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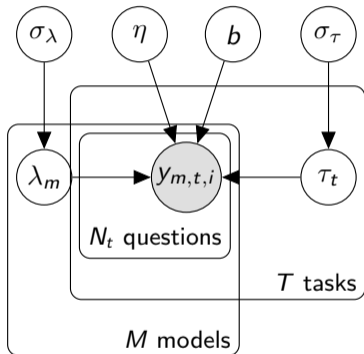
Task-based model.



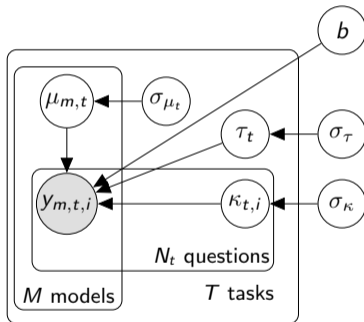
Question-task difficulty model.

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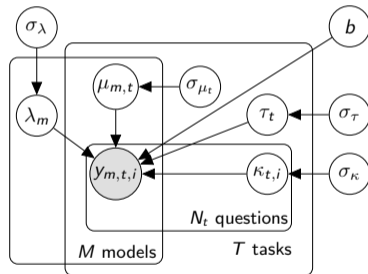
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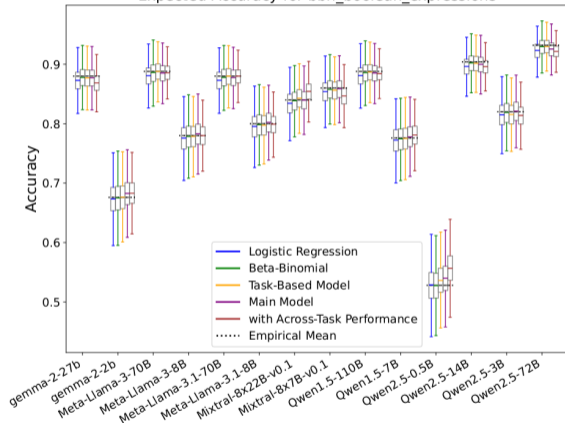


+ Across-task performance latent variable.

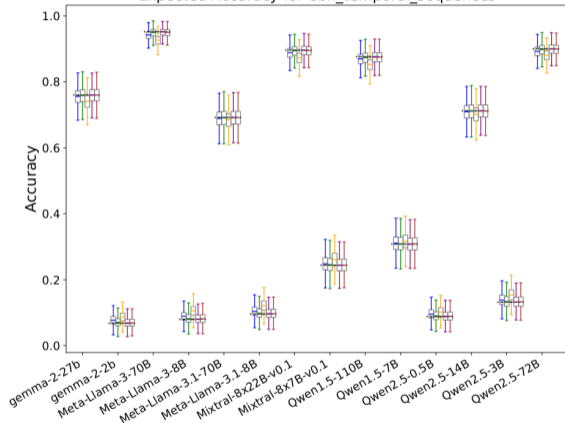
Graphical models of the proposed hierarchical models. **Way too complicated!**

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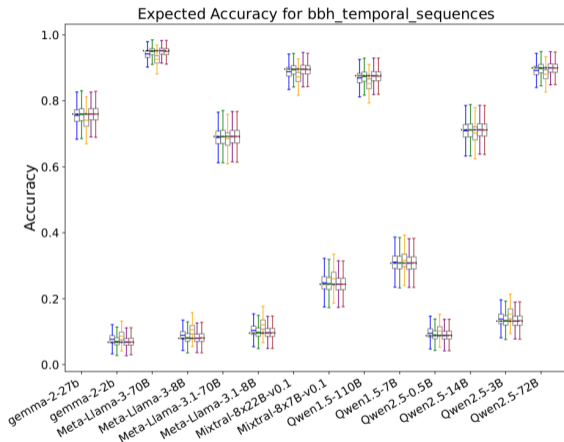
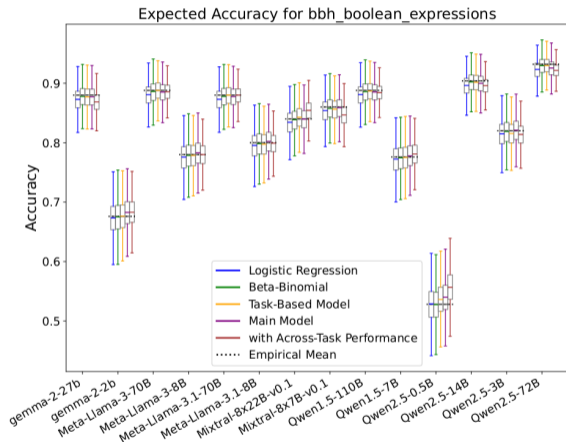
Expected Accuracy for bbh_boolean_expressions



Expected Accuracy for bbh_temporal_sequences



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So just use Beta-Binomial!

Future Directions

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- The results for this were interesting, but not as straightforwardly interpretable as we hoped.
- Perhaps these techniques could be used more successfully for predicting eval performance based on the mix of pretraining data?
- Or predicting the effectiveness of post-training on downstream evals?

Thank You

- Any questions?

References I



Bowyer, Sam, Laurence Aitchison, and Desi R. Ivanova (Oct. 2025). “Position: Don’t Use the CLT in LLM Evals With Fewer Than a Few Hundred Datapoints”. *en. In: Proceedings of the 42nd International Conference on Machine Learning*. ISSN: 2640-3498. PMLR, pp. 81143–81184. URL: <https://proceedings.mlr.press/v267/bowyer25a.html> (visited on 11/09/2025).



Bowyer, Sam, Thomas Heap, and Laurence Aitchison (Sept. 2024). “Using Autodiff to Estimate Posterior Moments, Marginals and Samples”. *en. In: Proceedings of the Fortieth Conference on Uncertainty in Artificial Intelligence*. ISSN: 2640-3498. PMLR, pp. 394–417. URL: <https://proceedings.mlr.press/v244/bowyer24a.html> (visited on 11/09/2025).

References II



Chatterjee, Sourav and Persi Diaconis (Apr. 2018). “The sample size required in importance sampling”. en. In: *The Annals of Applied Probability* 28.2. ISSN: 1050-5164. DOI: 10.1214/17-AAP1326. URL: <https://projecteuclid.org/journals/annals-of-applied-probability/volume-28/issue-2/The-sample-size-required-in-importance-sampling/10.1214/17-AAP1326.full> (visited on 02/03/2023).



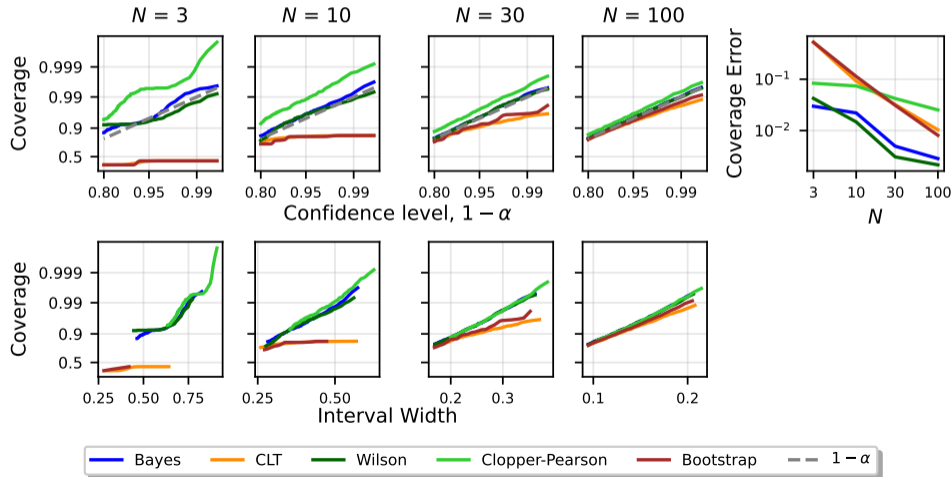
Heap, Thomas, Sam Bowyer, and Laurence Aitchison (July 2025). “Massively Parallel Expectation Maximization For Approximate Posteriors”. en. In: *Proceedings of the 7th Symposium on Advances in Approximate Bayesian Inference*. ISSN: 2640-3498. PMLR, pp. 25–66. URL: <https://proceedings.mlr.press/v289/heap25a.html> (visited on 11/09/2025).



Miller, Evan (Nov. 2024). *Adding Error Bars to Evals: A Statistical Approach to Language Model Evaluations*. en. arXiv:2411.00640 [stat]. DOI: 10.48550/arXiv.2411.00640. URL: <http://arxiv.org/abs/2411.00640> (visited on 12/17/2024).

IID Questions Setting: Prior Mismatch

Use $\theta \sim \text{Uniform}[0, 1]$ as the prior, but $\theta \sim \text{Beta}(100, 20)$ as the true data distribution.
($\mathbb{E}[\theta] = 0.83$ and $\text{Var}(\theta) = 0.034^2$.)



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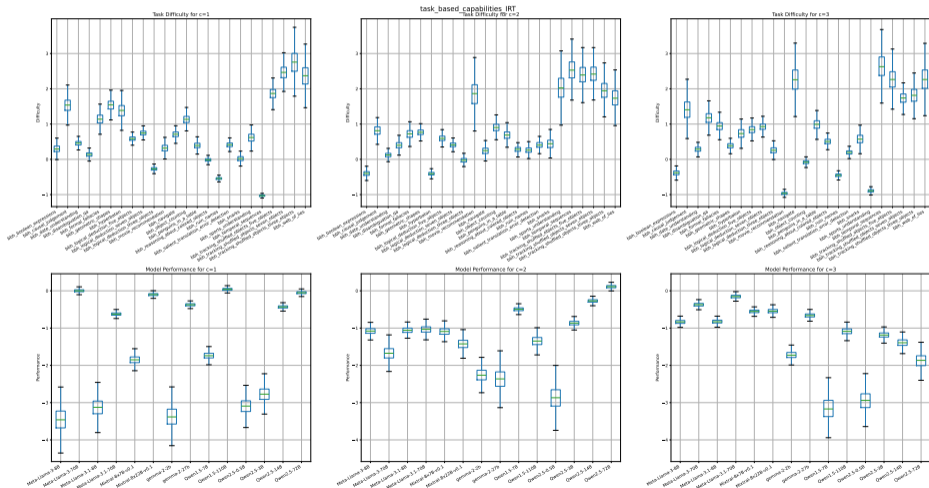
- Given eval questions and reponses, use an SAE-like model to enforce sparsity on features across the latent dimensions of 'model performance' and 'benchmark difficulty' vectors.

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Clustered Questions Setting: Bayesian Implementation

Snippet 4: Bayesian analysis for clustered evals

```
1 # S_t, N_t: np.arrays of length T with total
2 # successes & questions per task
3 import numpy as np
4 from scipy.stats import betabinom
5
6 # set number of samples, K
7 K = 10_000
8
9 # get K samples from the prior (with extra dimension for broadcasting over tasks)
10 thetas = np.random.beta(1,1, size=(K,1))
11 ds = np.random.gamma(1,1, size=(K,1))
12
13 # obtain weights via the likelihood (sum the per-task log-probs)
14 log_weights = betabinom(N_t, (ds*thetas), (ds*(1-thetas))).logpmf(S_t).sum(-1)
15
16 # normalise the weights
17 weights = np.exp(log_weights - log_weights.max())
18 weights /= weights.sum()
19
20 # obtain samples from the posterior
21 posterior = thetas[np.random.choice(K, size=K, replace=True, p=weights)]
22
23 # Bayesian credible interval
24 bayes_ci = np.percentile(posterior, [2.5, 97.5])
```