In particular, a Bayesian model can explicitly account for:

* Time. Perhaps old ratings should count for less than new ratings.
* Prior beliefs. Perhaps an unrated item from a bestselling author should appear above an unrated item from an unknown author.
* Attitudes toward risk. Exactly how risk-averse should the algorithm be about promoting items with a small number ratings?
* Step 1: Start with a made-up belief about each item's average rating
* Step 2: Update the belief as new data arrives
* Step 3: Use the newest belief to construct a sorting criterion for each item

They say they prefer Bayesian methods for two reasons:

1. Their end result is a probability distribution, rather than a point estimate. “Instead of having to think in terms of p-values, we can think directly in terms of the distribution of possible effects of our treatment…This makes it much easier to understand and communicate the results of the analysis.”
2. Using an informative prior allows them to alleviate many of the issues that plague classical significance testing (they cite repeated testing and low base rate problem – though Evan Miller disputed the latter argument on [this Hacker News thread](https://news.ycombinator.com/item?id=7815419))

In summary, the difference is that in the Bayesian view, a probability is assigned to a hypothesis. In the frequentist view, a hypothesis is tested without being assigned a probability.

* Bayesianism is built around beliefs. A “belief” describes the probability that we think some parameter takes each of a number of possible values. For our application, we'll have a belief for each item; a belief is a mathematical construct, but a typical belief might be verbalized as “There is a 50% chance that 10% of people or fewer like item A, and a 50% chance that more than 10% of people like item A.” Note that this belief is quite distinct from “There is a 100% chance that 10% of people like item A”.

1. **Group A – Group B**
2. **Sample Size – Estimated Time of Experiment**
3. **Sanity Check – Metrics**
4. **Practical and Statistical Significance**

if hour\_per\_week => 5 hours:

continue Free Trial

else:

go to Access Course Material

**Sources**

# [Is Bayesian A/B Testing Immune to Peeking? Not Exactly](http://varianceexplained.org/r/bayesian-ab-testing/)

**Beta**

**d\_min: practical significance**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **d\_min** | **Lower CI** | **Upper CI** | **Statistically Significance** | **Practically Significant** |
| **Enrollment Rate** | **0.01** | **-0.029** | **-0.012** | **Yes – does not contain zero** | **Yes – does not contain d\_min** |
| **Conversion Rate** | **0.0075** | **-0.011** | **0.0018** | **No – CI contains 0** | **No – CI contains d\_min** |

**User/Class = 10k**

|  |  |  |
| --- | --- | --- |
| **Conversion Rate** | **Probability** | **Additional Revenue** |
| **Experiment > Control** | **15.8 %** |  |
| **0.5% larger** | **6.43%** | **$1000** |
| **1% larger** | **2.78%** | **$2000** |
| **1.5% larger** | **0.92%** | **$3000** |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Conversion Rate** | | **Probability** | | **Additional Loss** | |
| **Experiment < Control** | | **84%** | |  | |
| **0.5% lower** | | **70%** | | **$1000** | |
| **1% larger** | | **53%** | | **$2000** | |
| **1.5% larger** | | **33.3%** | | **$3000** | |
| **May2017** | **Bank-Loss** | | **ML – Loss** | | **Difference** |
| **Missed Fraud** | 760,623 | | 372,837 | | 387,786 |
| **Declined Transactions** | 4,567,144 | | 3,896,693 | | 670,451 |
| **Total** | 5.2M | | 4.1M | | 1.1M |

|  |  |  |  |
| --- | --- | --- | --- |
| **TestDataset** | **Bank-Loss** | **ML – Loss** | **Difference** |
| **Missed Fraud** | 3,200,071 | 129,256 | 3,070,814 |
| **Declined Transactions** | 225,133 | 64,802 | 160,330 |
| **Total** | 3.4M | 194k | 3.2M |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Crime Rate** | **2003** | **2015** | **Overall** | **Bayesian** |
| **Mission** | 0.365 | 0.278 | 0.356 | 0.342 |
| **Tenderloin** | 0.188 | 0.296 | 0.243 | 0.208 |
| **Richmond** | 0.153 | 0.165 | 0.134 | 0.177 |
| **Bayview** | 0.294 | 0.261 | 0.266 | 0.273 |

The resulting distributions describe the estimated probability of different amounts of rain at a location for a select time interval (e.g. annual, seasonal or monthly), based on the historical values for that interval at that location.

The gamma distribution may range from exponential-decay forms for shape values near one, to nearly normal forms for shape values beyond 20 (Wilks, 1990; Ozt ¨ urk, 1981)

This study showed that the gamma distribution parameters can be scaled to describe rainfall for events of different duration. This is valuable because it means that the gamma distribution is useful for studying rainfall at a variety of timescales from multi-day accumulations to seasonal accumulations.

The Gamma Distribution is a distribution of waiting times between Poisson distributed events. I

For most problems of interest, Bayesian analysis requires integration over multiple parameters, making the calculation of a [posterior](https://en.wikipedia.org/wiki/Posterior_probability) intractable whether via analytic methods or standard methods of numerical integration.

However, it is often possible to *approximate* these integrals by drawing samples from posterior distributions. For example,:

we can use these values to approximate the unknown integral. This process is known as [**Monte Carlo integration**](https://en.wikipedia.org/wiki/Monte_Carlo_integration). In general, Monte Carlo integration allows integrals against probability density functions

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Pickup Rate** | **Jan15** | **May15** | **Overall** | **Bayesian** |
| **A** | 0.302 | 0.356 | 0.265 | 0.307 |
| **B** | 0.222 | 0.34 | 0.328 | 0.266 |
| **C** | 0.299 | 0.421 | 0.209 | 0.255 |
| **D** | 0.208 | 0.175 | 0.219 | 0.249 |