Monitoring Process Change with Bayesian Methods

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2 September 2015



Structure of Talk

- Discussion of Problem
- Bayesian Analysis and the Beta Distribution
- Adding Layers of Noise
- Distribution Distances and f-divergences



Monitoring Process Change

- NOT Change-point Analysis
- Time of change known want to measure change effect
- Have measured metrics
- Need to determine change vs noise
- Generic technique for the problem



Sales-call Conversions

- Assume a binary outcome
- Conversion rate of sales calls to actual sales
- Amount irrelevant
- Data summarised monthly
- Change due to internal improvements leading to faster turnaround



Sales-call Conversions

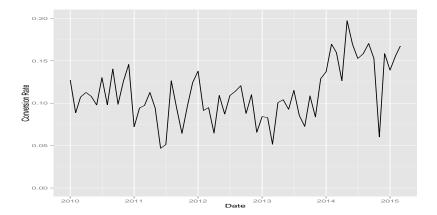
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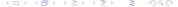


Generating Data

Want to generate time-series for θ , use normal distribution:







```
generate counts <- function(rate dt, month count) {
    rate dt <- data.table(rate dt. month count = month count):
    rate_dt[, conversion_count := mapply(rbinom, n = 1, month_count, underlying_rate)];
    rate dt[, conversion rate := conversion count / month count]:
    return(rate_dt);
generate_yearly_data <- function(rate_dt) {</pre>
    vear dt <- rate dt[, list(a = sum(conversion count), b = sum(month count - conversion count)),</pre>
                         by = list(data_year = format(rate_date, '%Y'))];
    year_dt[, c("cum_a", "cum_b") := list(cumsum(a) + 1, cumsum(b) + 1)];
    distrib_dt <- year_dt[, generate_beta_plot_data(cum_a, cum_b), by = data_year];</pre>
    return(distrib_dt);
```

Summary

R package: mcmortswap https://bitbucket.org/appliedai/mcmortswap

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Slides available on github:

https://github.com/kaybenleroll/dublin_r_workshops

