COHORT REVENUE & RETENTION ANALYSIS: A BAYESIAN APPROACH

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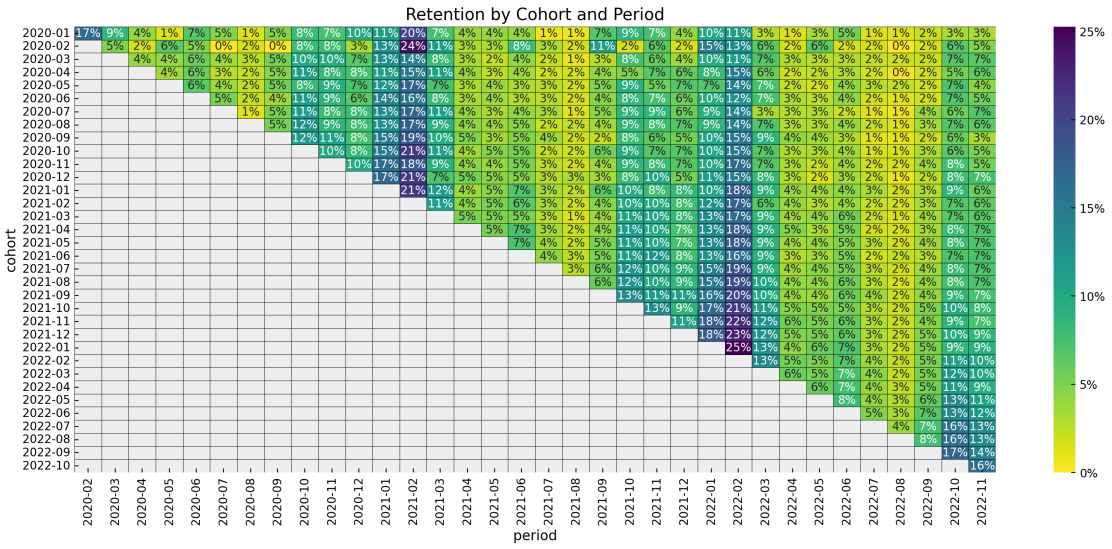
Abstract. We present a bayesian approach to model cohort-level retention rates and revenue over time. We user bayesian additive regression trees (BART) to model the retention component which we couple with a linear model to model the revenue component. This method is flexible enough to allow adding additional covariates to both model components. This bayesian model allow us to quantify the uncertainty in the estimation, understand the effect of the covariates on the retention through partial dependence plots (PDP), individual conditional expectation (ICE) plots and las but not least forecast the future revenue and retention rates.

Contents

1. Introduction



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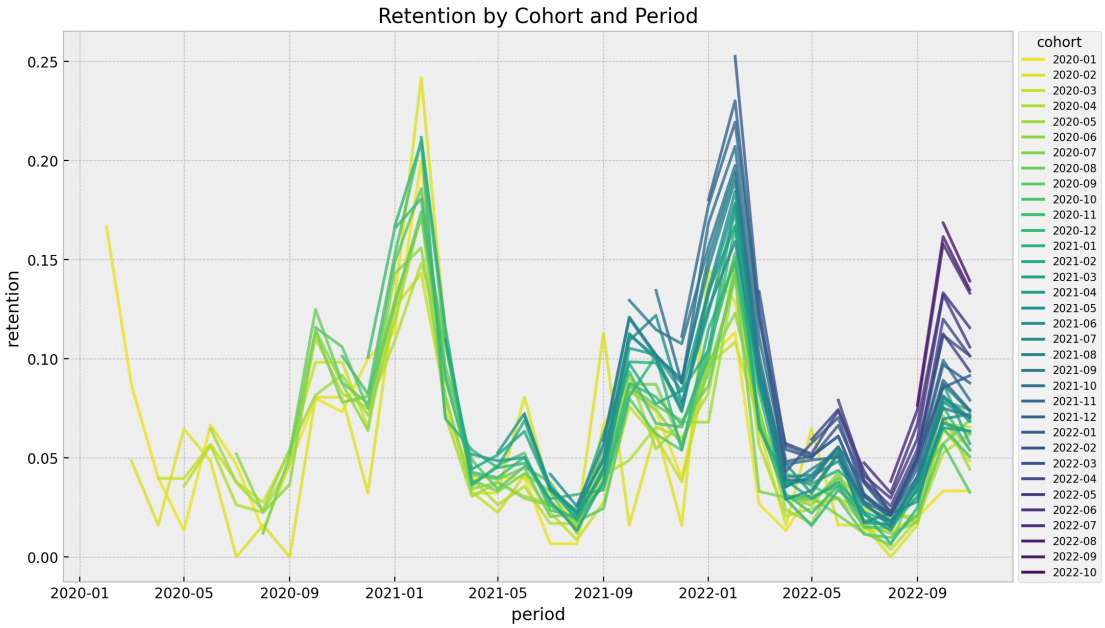


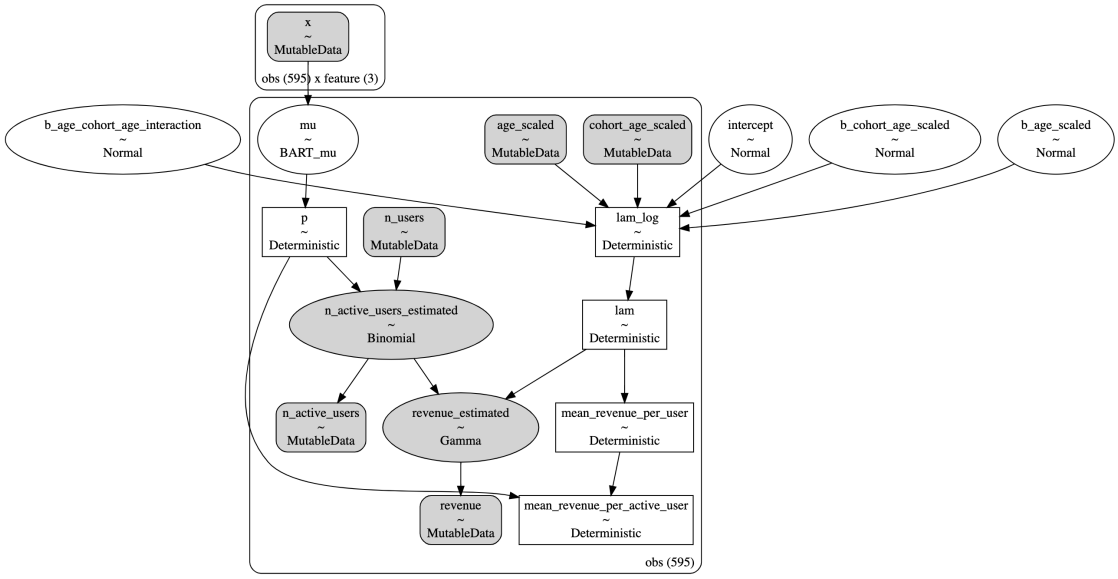
Appendix: Python Code

LISTING 1. Python example

```python
import pymc_bart as pmb
import pymc as pm


with pm.Model(coords={"feature": features}) as model:

    # --- Data ---
    model.add_coord(name="obs", values=train_obs_idx, mutable=True)
    age_scaled = pm.MutableData(
        name="age_scaled", value=train_age_scaled, dims="obs"
    )
    cohort_age_scaled = pm.MutableData(
        name="cohort_age_scaled", value=train_cohort_age_scaled, dims="obs"
    )
    x = pm.MutableData(name="x", value=x_train, dims=("obs", "feature"))
    n_users = pm.MutableData(name="n_users", value=train_n_users, dims="obs")
    n_active_users = pm.MutableData(
        name="n_active_users", value=train_n_active_users, dims="obs"
    )
    revenue = pm.MutableData(name="revenue", value=train_revenue, dims="obs")

    # --- Priors ---
    intercept = pm.Normal(name="intercept", mu=0, sigma=1)
    b_age_scaled = pm.Normal(name="b_age_scaled", mu=0, sigma=1)
    b_cohort_age_scaled = pm.Normal(name="b_cohort_age_scaled", mu=0, sigma=1)
```

```
    b_age_cohort_age_interaction = pm.Normal(
        name="b_age_cohort_age_interaction", mu=0, sigma=1
    )

    # --- Parametrization ---
    # The BART component models the image of the retention rate under the
    # logit transform so that the range is not constrained to [0, 1].
    mu = pmb.BART(name="mu", X=x, Y=train_retention_logit, m=50, dims="obs")
    # We use the inverse logit transform to get the retention rate
    # back into [0, 1].
    p = pm.Deterministic(name="p", var=pm.math.invlogit(mu), dims="obs")
    # We add a small epsilon to avoid numerical issues.
    p = pt.switch(pt.eq(p, 0), eps, p)
    p = pt.switch(pt.eq(p, 1), 1 - eps, p)

    # For the revenue component we use a Gamma distribution where we
    # combine the number of estimated active users with the average
    # revenue per user.
    lam_log = pm.Deterministic(
        name="lam_log",
        var=intercept
        + b_age_scaled * age_scaled
        + b_cohort_age_scaled * cohort_age_scaled
        + b_age_cohort_age_interaction * age_scaled * cohort_age_scaled,
        dims="obs",
    )

    lam = pm.Deterministic(name="lam", var=pm.math.exp(lam_log), dims="obs")

    # --- Likelihood ---
    n_active_users_estimated = pm.Binomial(
        name="n_active_users_estimated",
        n=n_users,
        p=p,
        observed=n_active_users,
        dims="obs",
    )

    x = pm.Gamma(
        name="revenue_estimated",
        alpha=n_active_users_estimated + eps,
        beta=lam,
        observed=revenue,
        dims="obs",
    )

    # --- Derived Quantities ---
    mean_revenue_per_user = pm.Deterministic(
```

```
        name="mean_revenue_per_user", var=(1 / lam), dims="obs"
    )
    pm.Deterministic(
        name="mean_revenue_per_active_user",
        var=p * mean_revenue_per_user,
        dims="obs"
    )
```



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