When features go missing, Bayes' comes to the rescue

Narendra Mukherjee

Machine Learning Scientist, Tripadvisor



About myself

- Machine Learning Scientist in Tripadvisor's B2C data science team
- Work in a variety of domains from sort & recommendations to NLP
- Previously: PhD in Neuroscience from Brandeis University; studied taste processing in the brain
- Long time Bayesian
- $\bullet\,$ Extras: avid bicyclist, $>\!\!10k$ miles logged in the Boston/Massachusetts area
- narendramukherjee.github.io



About Tripadvisor



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• How do missing values arise in a sorting task?



Problem: Missing values in model features

- How do missing values arise in a sorting task?
- Why do they hurt performance in a sorting task?



| Let's sort some products! | | | | | | | |
|---------------------------|-------|----------|------|-------------|-----------|--------|--|
| Products | Views | Bookings | CVR | Price (USD) | # Reviews | Rating | |
| Old Faithful | 1000 | 200 | 0.2 | 20 | 500 | 4.5 | |
| Expensive 'n Dazzling | 1000 | 50 | 0.05 | 200 | 600 | 4.5 | |
| New Kid on the Block | 100 | 10 | 0.1 | 50 | 0 | ??? | |
| Out of Season | 0 | 0 | ??? | 40 | 500 | 4.5 | |



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4-in-1 Cancun Snorkeling Tour: Swim with turtles, reef, statues and...

Discover four of the Yucatan's top underwater sights in just one morning during a snorkeling tour that's designed with anxious swimmers and firsttime snorkelers in mind. A guide is on hand to ensure you feel...read more

🕭 Taking safety measures

(a) 3-4 hours By: Total Snorkel Papelar: Backed by 971 travelers!





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We are the one the first Luxury yachts companys in cancun we have a Large fleet of yachts. Our crew will take you to the best places in the area. All our fleet is equiped with twin engines and well maintained,...read more

🅭 Taking safety measures

By: Cancun Yacht Rentals

Views: 5000 Books: 971 CVR: 0.19 Views: 5000 Books: 50 CVR: 0.01



\$560.00

More Info



4-in-1 Cancun Snorkeling Tour: Swim with turtles. reef. statues and... and and and reviews Discover four of the Yucatan's top underwater sights in just one morning

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A Taking safety measures (i) 3-4 hours



from



Views: 5000 **Books:** 971 **CVR:** 0.19

Views: 5000 **Books:** 50 **CVR: 0.01**

What if only 100 of the 5000 views were from users who selected a Yacht Rentals filter?





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- **2** $\text{CVR} = \frac{50}{5000} = 0.01$ or $\text{CVR} = \frac{50}{100} = 0.5$ if the list is being served to a user who has selected the **Yacht Rentals** filter?





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- **2** $\text{CVR} = \frac{50}{5000} = 0.01$ or $\text{CVR} = \frac{50}{100} = 0.5$ if the list is being served to a user who has selected the **Yacht Rentals** filter?
- **③** CVR is missing for product \times filter combinations that aren't viewed by users.

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- Tree-based models cannot extrapolate beyond their training data they usually make constant predictions outside the regime of what they've seen during training
- Bad predictions are *extremely visible* in a list of sorted recommendations it is not enough to be doing well "on average" as in other ML tasks





• Drop all rows with missing values



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 - KNN finding is impractical given the strict latency requirements of a recommender system. AirBnB blog post



Require: Initial imputation of missing values in {model features} by, say, their means **repeat**

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for feature<sub>i</sub> \in {model features} do

feature<sub>i</sub><sup>Not Missing</sup> \xrightarrow{\text{Train}} f(\{\text{model features}\}_{-i})

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 \boldsymbol{f} and Tolerance are defined by the user



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- Takes into account the relationships between the different features (only KNN is able to do this)
- Provides a model (f) that can scale up the imputation process
- User can modify f and Tolerance to tradeoff between imputation speed and quality

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Naive approach: Replace missing values for CTR/CVR of product \times filter combinations by -1 (lower than the minimum possible value of 0). Happens when # Views = 0



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| Products | Views | Bookings | CVR |
|--|---------|----------|-----|
| Tower of London Entrance Ticket Including Crown Jewels and Beefeater Tour | ≫ 0 | ≫ 0 | > 0 |
| Christmas Lights Tour of London | $\gg 0$ | $\gg 0$ | > 0 |
| Stonehenge, Windsor Castle, and Bath from London | ≫ 0 | ≫ 0 | > 0 |
| Private Walking Tour of London with Brazilian Portuguese Speaking Guide | 0 | 0 | -1 |
| Big Bus London Hop-On Hop-Off Tour | $\gg 0$ | ≫ 0 | > 0 |

Top 5 products for one of the Experiences' pages in London

CVR = -1

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Principled approach: Replace missing values using *IterativeImputer*

| Top 5 products for one of the Experiences pages in Eulaon | | | | | | |
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| Big Bus London Hop-On Hop-Off Tour | $\gg 0$ | $\gg 0$ | > 0 | | | |
| Warner Bros. Studio: The Making of Harry Potter with Luxury Round-Trip Transport from London | $\gg 0$ | ≫ 0 | > 0 | | | |

Top 5 products for one of the Experiences' pages in London



How/why does it work? Enter Bayes!



Probabilistic understanding of imputation

Think of a probabilistic graphical model with missing values (M) as latent (hidden) variables



Two extreme views of imputation:

- Forget about the relationships between the features, and model them as independent Gaussians ⇒ replace missing values by MLE, aka, sample mean
- Explicitly model the entire joint distribution of all features (Joint Modelling in statistics). Can only be done under restrictive assumptions

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Can we do better and strike a middle ground?

Instead of the full joint distribution:

P(Missing, Observed, Features) (1)

Model the *posterior* distribution of what we don't know (i.e, latent variables=missing values) *given* what we do know (i.e, the observed):

 $P(Missing|Observed, Features) \sim P(Observed|Missing, Features) \times P(Missing, Features)$ (2)

Full machinery of Bayesian inference can be applied to this problem!



Posterior inference using MCMC

PyMC3, by default, performs posterior inference over any missing values in the data Upcoming tutorial on this at PyMCon: Missing value tutorial



Task becomes even easier if we can sample from the conditional distributions of the features, i.e., $P(\text{Feature}_i | \{\text{Features}\}_{-i}) \rightarrow \text{Gibbs sampling}$



Approximate Bayesian inference



$$f_i \sim P(\text{Feature}_i | \{\text{Features}\}_{-i})$$

Ideal for expectation-maximization (EM): cycle between optimizing the "parameters" of conditional distributions, f_i , and latent variables (missing values, M) iteratively



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Ideal for expectation-maximization (EM): cycle between optimizing the "parameters" of conditional distributions, f_i , and latent variables (missing values, M) iteratively Guaranteed to find a local maximum of the posterior P(Missing|Observed, Features)



Approximate Bayesian inference: different flavors of EM

Variational inference ("fully" Bayesian): Maintain the conditional distributions over the parameters of f_i and for the latent variables M at every iteration - all estimates are averaged wrt these conditionals



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- Iterated Conditional Modes (ICM): Set all random variables to the MAP/MLE estimate at each iteration, no distributions are maintained. eg: K-Means clustering



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Require: Initial imputation of missing values in {model features} by, say, their means (Setting a prior over the missing values)

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Known in the statistics community as Multiple Imputation with Chained Equations (MICE) StackOverflow, MICE

A word of caution

- ICM can get stuck in local optima multiple random restarts are needed
- ML: pick the best (by MLE etc) fit amongst the multiple runs. Statistics: use the restarts to get confidence intervals on the estimates ("multiple" in MICE)
- We got reasonably good results in the missing value imputation problem with even just 1 run



Thank you!!

Visit narendramukherjee.github.io

