2017 Data Mining Cup

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Overview

Section 1

Introduction

2017 Data Mining Cup

Task released April 5th

- Use historical data to predict revenue for an online pharmacy
- Train on 90 days of user actions
- Predict revenue for each user action over subsequent 30 days
- Model with smallest squared error $\sum_i (r_i - \hat{r}_i)^2$ wins
- Predictions due May 17th

Training Data

	lineID	day	pid	adFlag	availability	competitorPrice	click	basket	order	price	revenue
1	1.00	1.00	6570.00	0.00	2.00	14.60	1.00	0.00	0.00	16.89	0.00
2	2.00	1.00	14922.00	1.00	1.00	8.57	0.00	1.00	0.00	8.75	0.00
3	3.00	1.00	16382.00	0.00	1.00	14.77	0.00	1.00	0.00	16.06	0.00
4	4.00	1.00	1145.00	1.00	1.00	6.59	0.00	0.00	1.00	6.55	6.55
5	5.00	1.00	3394.00	0.00	1.00	4.39	0.00	0.00	1.00	4.14	4.14
6	6.00	1.00	3661.00	0.00	1.00	13.66	0.00	0.00	1.00	10.03	10.03
7	7.00	1.00	3856.00	1.00	1.00	3.03	0.00	0.00	1.00	3.58	3.58
8	8.00	1.00	16963.00	0.00	1.00	8.78	1.00	0.00	0.00	8.75	0.00
9	9.00	1.00	14560.00	0.00	1.00	10.84	1.00	0.00	0.00	12.04	0.00
10	10.00	1.00	4853.00	1.00	1.00	9.12	1.00	0.00	0.00	8.75	0.00

What do the data look like?

Training Data – train.csv

- Each of 2,756,003 rows is one user action for one product
  - click, basket, or order
- `revenue`, a multiple of `price`
- Other features:
  - day, adFlag, availability, price, competitorPrice
- No feature to identify distinct users

Test Data – class.csv

- Same structure as above, excluding user action and `revenue`
- 1,210,767 rows

What do the data look like?

Items Data – items.csv

- Each of 22,035 rows is one item
- Information that doesn't change over time
- Linked to other data sets by product ID
- Other features:
  - manufacturer
  - group ("product group")
  - content, unit
  - pharmForm, genericProduct
  - salesIndex ("dispensing regulation code")
  - category, campaignIndex
  - rrp

Section 2

Exploration Results

Initial Results

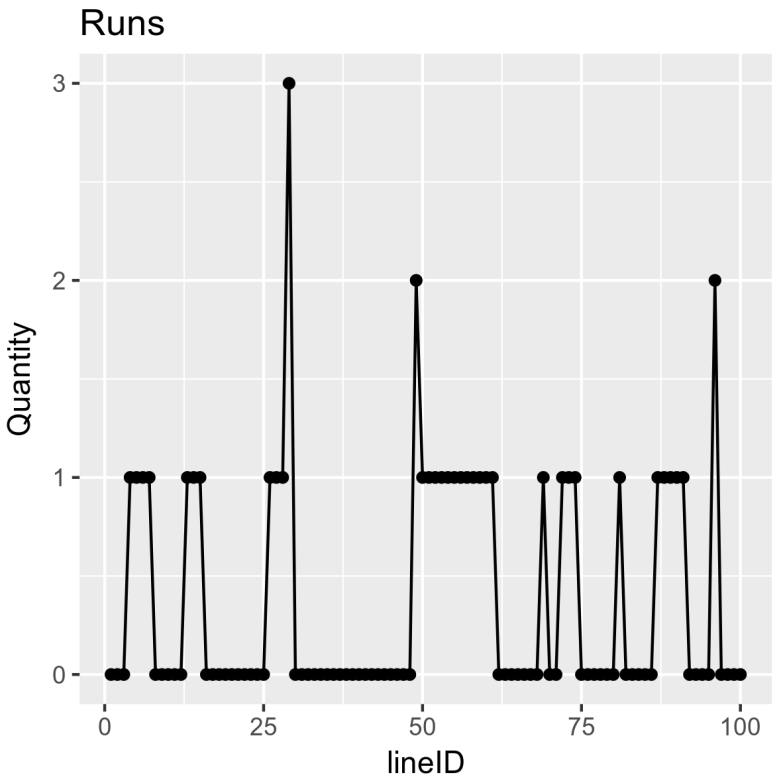
User Actions

- For each unique user and item, only the final action is recorded
- `competitorPrice` is missing for 3.7% of training data

Items

- Items with `availability` 4 rarely ordered—"out of stock"?
- Only 5.1% of items in training data have `salesIndex` 44 or 52
- 3,814 items are identical to another item, excluding ID

A Suspicious Pattern



A Suspicious Pattern

Curiouser and curiouser!

- Runs of "no order" and "order"
- "No order" run-lengths appear to have geometric distribution
- "Order" run-lengths usually less than 10
- Items rarely appear more than once within an "order" run

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Each "order" run might be a single shopping basket!

Additional Results

3-character codes in `pharmForm`

- Example: TAB, CRE, KAP, GLO, TRO
- Identifies form of medicine (tablets, syrup, salve, ...)
- German abbreviations, as listed on:
  - DocMorris
  - KohlPharma
- Closely related forms can have distinct codes

Section 3

Feature Engineering

Feature Engineering

Winning teams from many data mining competitions—including the UC Davis 2016 DMC team—say feature engineering was the most important part of their strategy.

Planned Features

- Day of week, day of month, week of month
- Windowed statistics
- Unit type (weight, volume, or pieces)
- Total units (from `content`)
- Price per unit, `competitorPrice` per unit, `rrp` per unit
- Grouped forms (from `pharmForm`)
- ...

Encoding Categorical Features

One-hot encoding

- Each category becomes a separate binary feature
- Models can eliminate unimportant categories
- Unhelpful when novel categories appear in the training data

Likelihood encoding

- For each category, each observation is assigned a likelihood
  - Likelihood is leave-one-out estimate of order probability
  - Likelihood is 0.5 for all observations in test data
- Loses information and doesn't account for order quantity

Section 4

Potential Models

Our Plan

- Generate lots of features
- Use initial model to select important features
  - Importance rankings—from random forest, for example
  - Lasso or other regularization methods
- Build an ensemble of models and refine initial model

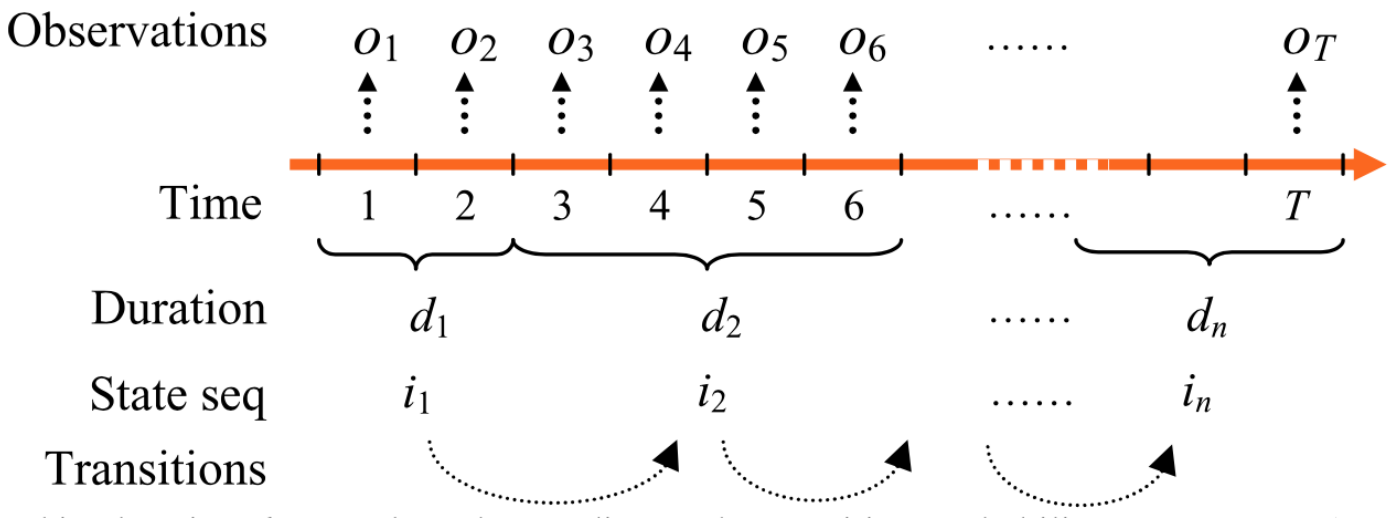
Choosing Models

We need advice on which models to use!

Proposed Models

- Quantity
  - Hidden (semi-)Markov model
  - Linear-chain conditional random field
  - Generalized linear models
  - Boosted random forest
- Revenue

Hidden Markov And Semi-Markov Models



Hidden Markov And Semi-Markov Models

Hidden Markov Model (HMM)

- Each response y_i comes from one of several subpopulations
- Subpopulations may have different distributions
- An unobserved Markov chain determines which subpopulation

Hidden Semi-Markov Model

- Generalization of HMMs
- Time in a state can affect transition probabilities

Advice? Suggestions?