Delayed Feedback Model with Negative Binomial Regression for Multiple Conversions

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# OUTLINE

INTRODUCTION

PROPOSED MODEL

**EXPERIMENT RESULTS** 

RECAP

# INTRODUCTION

#### Goal

- Predict the **eventual number of conversions** accurately.
- Input X: feature(User, Site, Ad), Target Y: the number of conversions

### Challenge

- Long delay between click and conversions
- Multiple occurrences of conversions

#### Contribution

- Cover multiple conversions and delay simultaneously
- Reasonable and easy to be implemented

Conversion Type	Non-binary ratio(%)	
Type A	26.4%	
Type B	1.1%	
Type C	0.0%	
Type D	59.3%	

Modeling Delayed Feedback in Display Advertising (Chapelle, 2014)

	Conversion	Delay	
DFM	Binary Logistic Regression	An exponential distribution	
NBDFM (Our Model)	Countable Negative Binomial Regression	Order Statistics	

# PROPOSED MODEL



## **PROPOSED MODEL - Notation**



X: a set of features

 $Y \in \{0, 1, ...\}$ : the number of conversions at the current timeY = 2 $C \in \{0, 1, ...\}$ : the number of eventual conversionC = 4 $D_k$ : the delay between click and the  $k^{th}$  conversionC = 4

E : the elapsed time since the click

## PROPOSED MODEL - NBDFM

#### **Objective Function**

- Negative log-likelihood of observed samples
- Suppose we observe n samples,  $\{x_j, a_j, d_{j1}, \dots, d_{ja_j}\}_{j=1}^n$

• 
$$L(w_c, w_d) = -\sum_{j=1}^n \log(\Pr(Y_j = a_j, D_{j1} = d_{j1}, \dots, D_{ja_j} = d_{ja_j} | X_j = x_j, E_j = e_j))$$

### Optimization

- Estimate parameters by minimizing our objective function
- Use L-BFGS as an optimizer

#### Prediction

• 
$$E(C|X = x) = \frac{p(x)}{1 - p(x)}$$
, where  $p(x) = (1 + \exp(-w_c x))^{-1}$ 

## PROPOSED MODEL - Models

Probability of conversion Pr(C = k | X = x)

• A standard negative binomial regression model

• 
$$Pr(C = k | X = x) = p(x)^{k}(1 - p(x))$$
 with  $p(x) = (1 + exp(-w_{c}x))^{-1}$ 

#### Joint probability of delays between click and multiple conversions $D_1, \dots, D_k$

• Order statistics of i.i.d random variable following an Exponential distribution

• 
$$Pr(D_1 = d_1, \dots, D_k = d_k | X = x, C = k) = k! \lambda(x) \exp\left(-\lambda(x) \sum_{i=1}^k d_i\right)$$
 with  $\lambda(x) = exp(w_d x)$ 

parameter vector

## PROPOSED MODEL - Sketch to calculate log-likelihood

## PROPOSED MODEL - Sketch to calculate log-likelihood

$$\begin{aligned} \text{line 1} \quad Pr(Y = a, D_1 = d_1, \dots, D_a = d_a | X = x, E = e) \\ \text{line 2} \quad = \sum_{k=a}^{\infty} \left\{ Pr(Y = a, D_1 = d_1, \dots, D_a = d_a | C = k, X = x, E = e) \right\} \\ \text{line 2-a} \quad Pr(Y = a, D_1 = d_1, \dots, D_a = d_a | C = k, X = x, E = e) \\ \text{line 2-b} \quad = Pr(D_1 = d_1, \dots, D_a = d_a, E < D_{a+1} < \dots < D_k | C = k, X = x, E = e) \\ \text{line 2-c} \quad = k! \lambda(x)^a exp(-\lambda(x) \sum_{i=1}^a d_i) \int_e^{\infty} \dots \int_{d_{k-1}}^{\infty} \lambda(x) exp(-\lambda(x) d_k) \dots d(d_k) d(d_{a+1}) \\ \text{line 2-d} \quad = a! \lambda(x)^a exp(-\lambda(x) \sum_{i=1}^a d_i) \left(\frac{k}{k-a}\right) exp(-(k-a)\lambda(x)e) \end{aligned}$$

line 3 = 
$$\sum_{k=a}^{\infty} a! \lambda(x)^a exp(-\lambda(x) \sum_{i=1}^a d_i) {k \choose k-a} exp(-(k-a)\lambda(x)e)p(x)^k(1-p(x))$$

By the negative binomial theorem

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$$\lim 4 = a! \,\lambda(x)^a exp(-\lambda(x)\sum_{i=1}^a d_i) \,(1-p(x)) \left( \sum_{j=0}^\infty \binom{j+(a+1)-1}{j} (p(x) exp(-\lambda(x)e))^j \right) \longrightarrow \left( \begin{array}{c} (1-p(x) exp(-\lambda(x)e))^{-(a+1)} \\ (1-p(x) ex$$

# **EXPERIMENT RESULTS**



## EXPERIMENT RESULTS - Dataset Settings

- **No public dataset** for evaluate multiple conversions
- Thus, we used LINE's real-traffic logs
- 21 days for training set, following day as test set
- **Repeated 7 times** to check consistency of the results



# EXPERIMENT RESULTS - Metrics and Competing Models

### **Evaluation Metrics**

Mean Squared Error (MSE)

MSE = 
$$\frac{1}{n} \sum_{j=1}^{n} (c_j - E_j)^2$$

Calibration

Calibration =  $\frac{\sum c_j}{\sum E_j}$ 

### Competing Models

- DFM
- GLMs
  - Logistic / Poisson / Negative Binomial
- DFM + Poisson: Heuristic
- Oracle GLMs: Upper bound



Training Data

#### Overall weighted metric

- Results of different models on 7 test days
- The column 'Diff' shows the difference of MSE between the given model and DFM

		MSE	Diff	Calibration(%)
Delay only	DFM	0.09219		141.77
	Logistic	0.09231	-0.00012	146.60
Count only	Poisson	0.08681	0.00537	108.85
	Negative Binomial	0.08682	0.00536	108.19
	DFM + Poisson	0.08723	0.00496	106.25
Count + Delays	NBDFM	0.08454	0.00764	101.12
	Oracle Logistic	0.09223		140.82
Upper bound	Oracle Poisson	0.08298		100.34
	Oracle Negative Binomial	0.08248		99.29



Multiple Conversions

Multiple Delays

Together

- Solve the real-world conversion prediction problem, the key to successful RTB auction
- Introduce a method NBDFM which allows to model both multiple conversions and delays jointly
  - Negative Binomial
  - Order Statistics
- Achieve a **significant improvement** in experiments
- Powerful but **simple to deploy** on production services



### Thanks

