User Choice Prediction

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https://youtu.be/NgvhkAReN4g

Motivation & Objectives

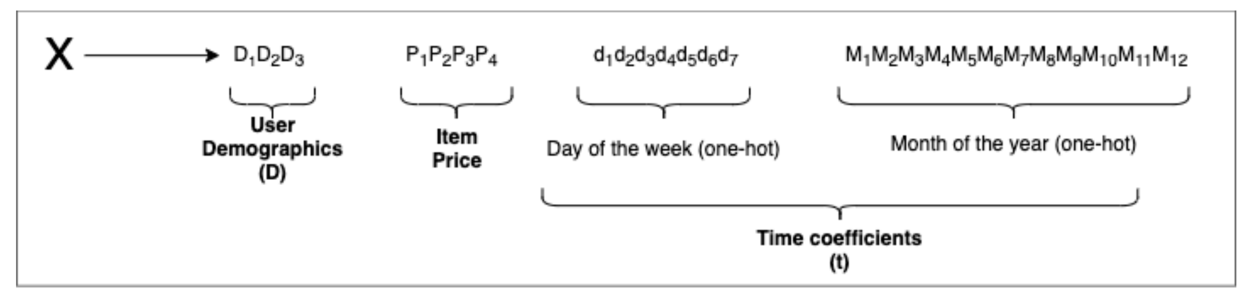
- Goal is to predict consumer choice given consumer purchase history along with some observables of consumers and items and price, time of day, day of week information and so on.
- We explored multinomial logit models, basic Neural net models, followed by multi-task learning models with and without embedding and also Bayesian embeddings.
- Building Neural networks with embeddings for these problems was challenging due to data constraints.
- The best model gives nearly 92.69% accuracy, with 2% improvements over the state-of-the-art Bayesian embedding model.

Datasets

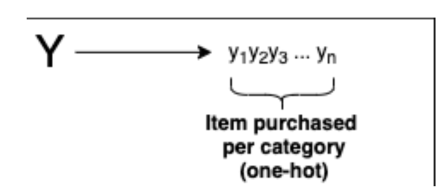
- We are using a novel dataset (~10 GB) from Susan Athey's Lab at Stanford GSB, on **user shopping choice** derived from multiple grocery stores in a large geographical region.
- The data contains complete billing information for a store on each day including information about transaction id, date, user id (from loyalty card logs), item id, price and quantity.
- We have partial user observables which includes generic personal attributes.
- And, also some information about items and information about their hierarchical classification into groups (typical examples are fruit, milk, detergent).

Features

- Our model belongs to the class of basic collaborative filtering models, except that our problem comes with **repeated choice** and more structure.
- We use a demographic **user feature** which is whether the user is married only present for 10% of users.
- Another feature we derive from the data is the tercile of every user for **the number of items** they purchase given a visit.
- modeling choice per category **encodes category information** much like a feature vector would to incorporate the item features.
- We use the following time features: month of year, week of year and day of week.

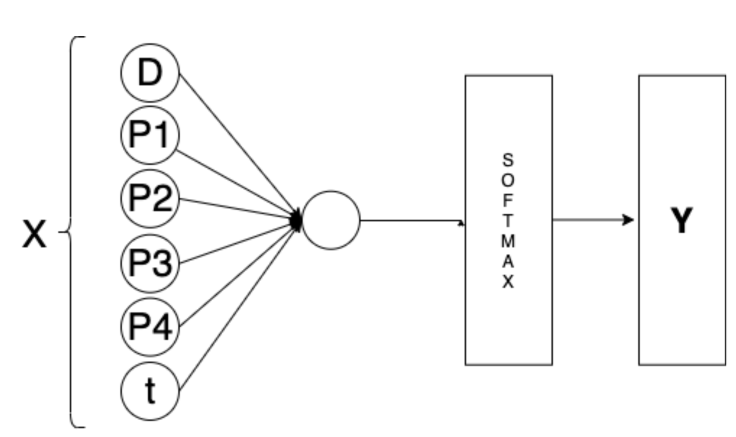


Input Feature Vector

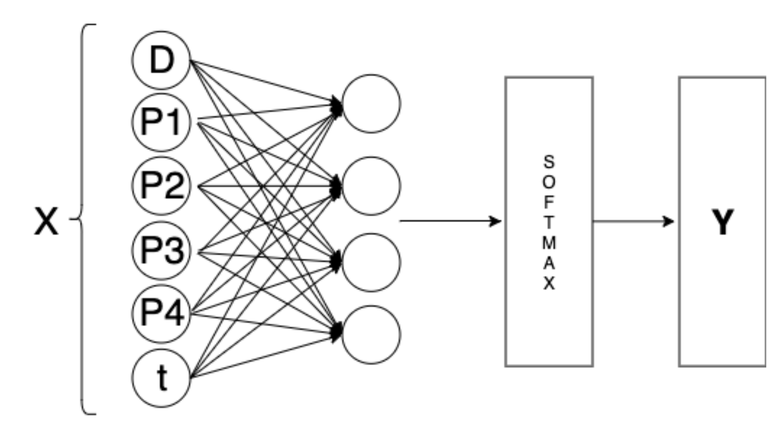


Output Feature Vector

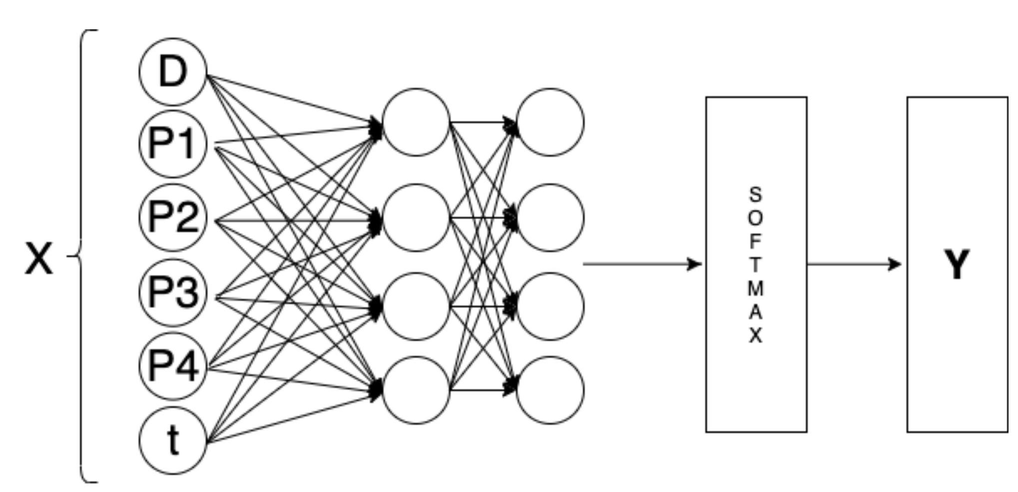
Model Architecture



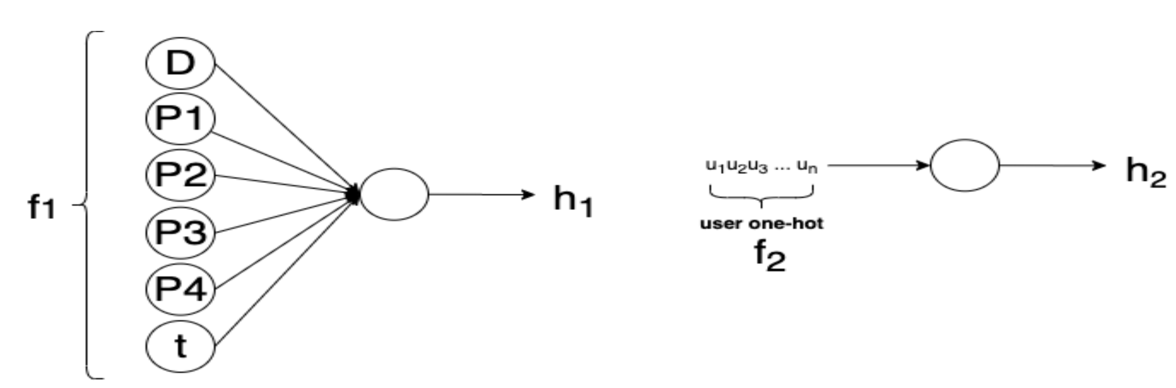
Basic Multinomial logit



MLP with 1 hidden layer

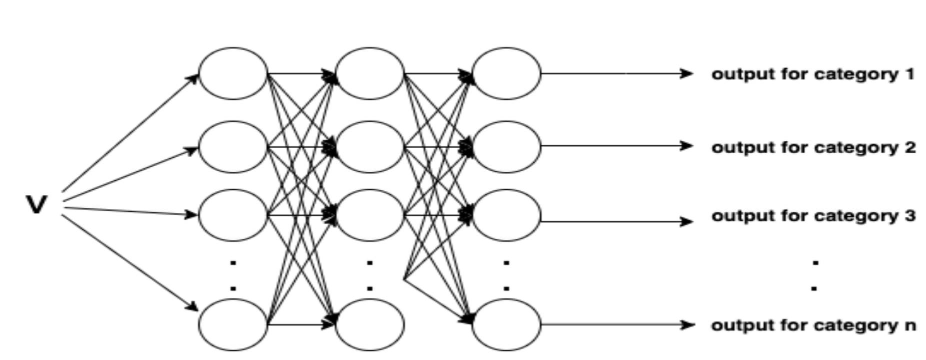


MLP with 2 hidden layer



$h_3 = h_1 \,.\, h_2$ $\quad$ $v = \text{concat}(h_1, h_2, h_3, h_4)$

$h_4 = \text{concat}(f_1, f_2)$



Multi-Task Learning with Embeddings

Results

The numbers are calculated per category and weighted by number of purchases for each category.

Model	Log Likelihood	Accuracy	Precision	Recall	F1
baseline_item_freq	-0.284942	0.917270	0.855519	0.917270	0.882245
baseline_user_item_freq	-0.282097	0.923744	0.902912	0.923744	0.908003
basic_mnl	-0.379898	0.917270	0.507557	0.534546	0.519109
multilayer_mnl	-0.328202	0.918198	0.519576	0.535474	0.525645
unrestricted_mnl	-0.264767	0.924011	0.689506	0.718780	0.698052
multilayer_mnl_two_layer	-0.245823	0.925648	0.691126	0.720417	0.705042
multilayer_mnl_one_layer	-0.240314	0.926139	0.701658	0.720907	0.705855
multitask_basic	-0.274243	0.918732	0.879776	0.918732	0.889628
multitask_user_onehot	-0.237934	0.926906	0.904628	0.926906	0.909831
multitask_embeddings	-0.236758	0.926886	0.904936	0.926886	0.910115
one level bayesian embeddings	-0.244352	0.925208	-	-	-
two level bayesian embeddings	-0.243596	-	-	-	-

Table 1: Test Set Results

Discussion & Future Work

- There had been no deep learning models being used for this problem so far.
- We also observe that the baseline model on user-item frequency performs better than the basic and unrestricted MNL models.
- In the series of models we designed, the best performing multi-task model with user embeddings beats state of the art embedding models which is a non-deep learning model.
- We are currently investigating the utility of this model in the real world.
- An exciting point of difference is how counterfactual accuracy would compare for our deep learning models versus current state of the art models.

References

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