

Price Prediction in a Trading Agent Competition

Tell travel agent preferences and agent tries to get as close as possible. Future traveling agent tries to meet preferences as little cost.

S: nowadays, tremendous drop in business for travel agents from online competition.

A: So in the very close future, everybody will ... ☺

University of Michigan: a TCA competition to design online agents capable of bidding on complementary and substitutable good. Hotels on same day going to be there.

TAC Travel Shopping game: each agent gets 8 clients, each which has 3 entertainments,

Flights: $1 \leq i \leq j \leq 5$

That means trip can be 1-5 days

Agents receive a random allocation of tickets. Can either allocate tickets to clients or could buy and trade, whichever would minimize.

28 auctions going on. 8 for hotels, 8 for flights (inflight and outflight = 2, * 4). 12 (3*4 for entertainment)

Every minute a hotel auction issues quotes.

Every minute starting at minute 4 one hotel chosen at random to close.

Feasible package: $p_a < p_d$ (preference for arrival be before that of departure)

Same hotel all nights

At most one 1 entertainment per night

Goal: maximize the following:

$$V_c(r) = 1000 - 100(|p_a - in_r| + |p_d - out_r|) + hp * H_r + \phi(r)$$

Flights: in range 250-400 with random changes, probability that will increase so want to buy as early as possible.

But Hotels close (auction for a room closes – 16 rooms in a hotel per night) as soon as 4 minutes and on. So have to predict prices, because need bid in before 4

Why is price prediction important?

Say it is a separate component of the whole thing. Divide into initial (before any auctions close) and interim (methods employed after).

In initial, all have is prices, and history. This paper focuses only on initial price prediction.

Organization of Tournament: 19 agents playing 440 games, weights increased each day.

Top 16 advanced to semifinals.

Semifinals: Heat1: 1-4 and 13-16

Heat 2: 5-12

Each 8 playing 14 games and lowest score dopped

Top 4 from each advanced to finals.

Finals: 32 games

Chart with results of Tournament, with scores, affiliations.

S: Note can win each game up to 1000. Yet final scores making around 3200 for 32 rounds, so not doing so well.

Price Prediction Survey: How many of agents actually used price prediction.

S: such a complicated game, how get anything for the science? So survey to see what each thing they are doing.

16/19 responded.

13/16 explicit price prediction

2/16: price prediction part of agent design, but not developed sufficiently to be used

1/16: no price prediction

Table 2: form of result and what approach used to get: machine learning. Historical. Comparative. Result as prob, point, priceline.

Point predictions: exact value

Prib distribution over prices: p of each price occurring

Priceline: Price per demand

Point vs Prob Distribution: Using means found superior to prob distribution by 3 diff research groups. Why? Speculation: due to incorrect usage of distribution. Prob distribution gives more info, and you can get mean from that prob distribution.

Q: also not enough sample,

S: right, so only have an approximation to distribution.

Info Employed: All info from past games, initial flight prices, and preferences of randomly generated clients.

All except Wolverine used historical data.

3 used flight prices.

Wolverine factors in own client preferences as part of **equilibrium calculations**.

ATTac is only one that takes advantage of identity of the agents. Which became available during semifinals and finals.

3 approaches to price predictions:

Historical Averaging: based on past games

Differed on how used. Most used games from seeding round

Cuhk used moving average

Southampton Tech: during seeding round, partitioned data into competitive, non-competitive, and semicompetitive.

Reference price for each day and hotel as specified in each game category.
During a game use that info to decide how to act

Machine Learning: Attac and kavayaH

Derived relationships between observable parameters. Used to predict hotel prices.

Competitive Analysis (Wolverine, from authors of this paper)

Assume: TAC markets well approximated by competitive economy.

Calculated Walrasian Competitive Equilibrium. Set of prices at which all prices would clear.

S: If know max each would pay, can know what price to set. Here all have it what they are saying. Economics – way to figure out how to figure out what willing to pay by what they are saying. Walrasian approach is such an attempt. Idealized view of what people will be doing. Can see paper for more info.

Table 3: Predictions: Predicted price vectors for each agent.

S: The Auction is such that overbidding does not hurt, since paying based on 16 lower down. To see how affect, see where are in terms of the mean.

Evaluation: Prediction quality accuracy measure: One is Euclidean distance.

Problem with Euclidean distance is that it tests for accuracy in an absolute sense. But perhaps if predictions are not so close, perhaps value of predicting closer does not increase.

Rather, use Expected Value of Perfect Predictive. VPP measures how much would gain by predicting better. Expected VPP does this outside of any specific client.

Then shows figure 1: graph of Euclidean distance to actual prices vs. expected VPP, with best fit line to the points.

S: To be cynical. Trick to writing it up is finding a metric which shows you did well. “We did very well with price prediction.” Even though did not win competition. Shows that don’t necessarily need to do great price prediction to succeed. Or perhaps dominant strategy is to buy flights cheaply very early and pay whatever price need to for the hotels to match.

Performed t-tests. Comparing agents to each other. Wolverine and ATTack01 only agents to beat “Best EVPP” Wolverine only one to significantly beat Best Euclidean distance.

Here did right thing to compare it to show that unlikely this is some artifact of experiment.

The Influence of Flight Prices:

The three best predictors are those that take flight price into account. Flight prices affect demand for trip days, and that demand affects trip prices.

Made 3 different versions of Wolverine: 1 ignores client knowledge, one ignores flight prices but takes the mean, and the third is a combo of above two.

Calculated EVPP for all 3. and saw just went up slightly when ignored client knowledge to get importance of each type of knowledge.

Limitations:

This focused exclusively on initial price prediction. Because easier. In future, interim.

Conclusions: Introduced EVPP and taking initial flight prices into account predict hotel prices more accurately. Shown that deriving shape of market from idealized economic theory just as accurate as is machine learning.

Authors admit competitive equilibrium not best possible model, but combine other elements as well.

D: only initial prices, and results show not such great results. Also only with flight prices included is it competitive.