Predicting Demand in Three Sided Marketplace

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Marketplace Dynamics

Three sided market: consumers, merchants, dashers

Journey of an order

- Consumer opens App
  - Forecast web traffic
- Consumer sees restaurants with delivery time estimates
  - Predict delivery times
- Consumer selects a Merchant and creates an order and checks out
- Order gets offered to and accepted by the Merchant
- Order gets offered to and accepted by a Dasher
  - Assignment algorithm consumes forecasts for dashers
- Order is prepared by the Merchant
  - Predict food preparation time
- Order is picked up by Dasher
- Order is delivered to Consumer
  - Dynamic delivery time prediction
- Consumer may contact DoorDash Support if there's an issue
  - Forecast number of support tickets

Different Demand Forecasts

Consumer Volume Hourly

- Hour by hour
  - For tracking and pacing
- 1 week out
  - To keep accuracy high
- Cut by submarket
  - Very granular geographical cuts, e.g. up to zip code

Consumer Volume Daily

- Day to day
- 7 days out
- Cut by business line
- Manual inputs
  - Requires back and forth with finance on endogenous factors (e.g. promotions) and exogenous factors (e.g. weather)
- Enables balancing
  - Can do inter-day demand and supply shaping and create accountability around actions

Consumer Volume Weekly & Annual

- Week to week / Every quarter
- 6 weeks out / 4 quarters out
- Cut by business line & city / business line & country
- Manual inputs
- Enables balancing

Problem

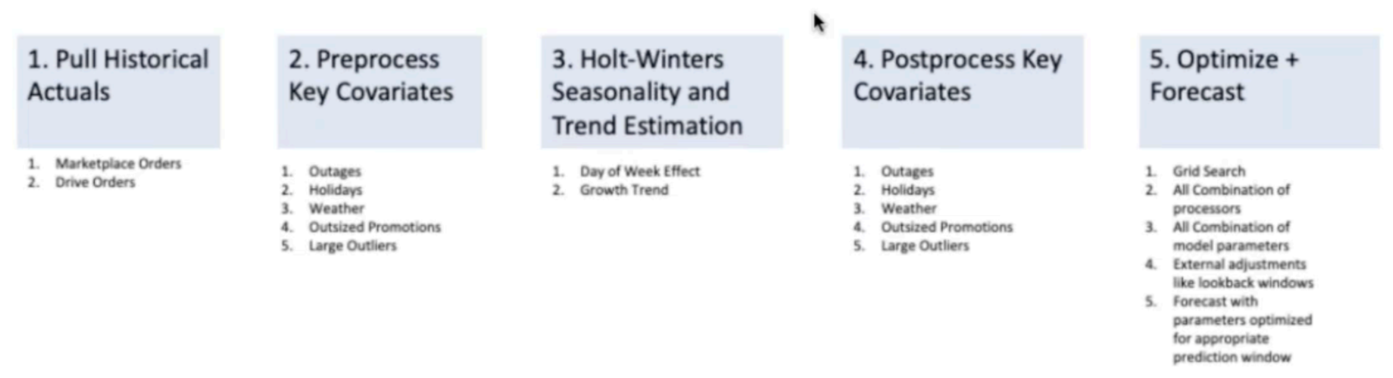
Previous methodology used WoW from prior years to forecast
This requires lots of adjustment

Solution

Implemented a decomposed time series methodology

- First decomposes historical volume into current course and speed by removing the effects of key volume covariates
- Then applies a Holt-Winters exponential smoothing model to estimate current business trend and seasonality
- And finally layers back in the effects of key covariates

Model Architecture



Note the advantages

- Current course and speed volume effects can be separated from estimation of complex interacting patterns like weather or holidays
- This is helpful given the limited number of observations

Results

- Saw a 13.6% relative volume weighted daily MAPE improvement
- This improvement is present even with known issues in weather, promotion, and monthly seasonality processing so we still have more room to improve

Annual Forecast

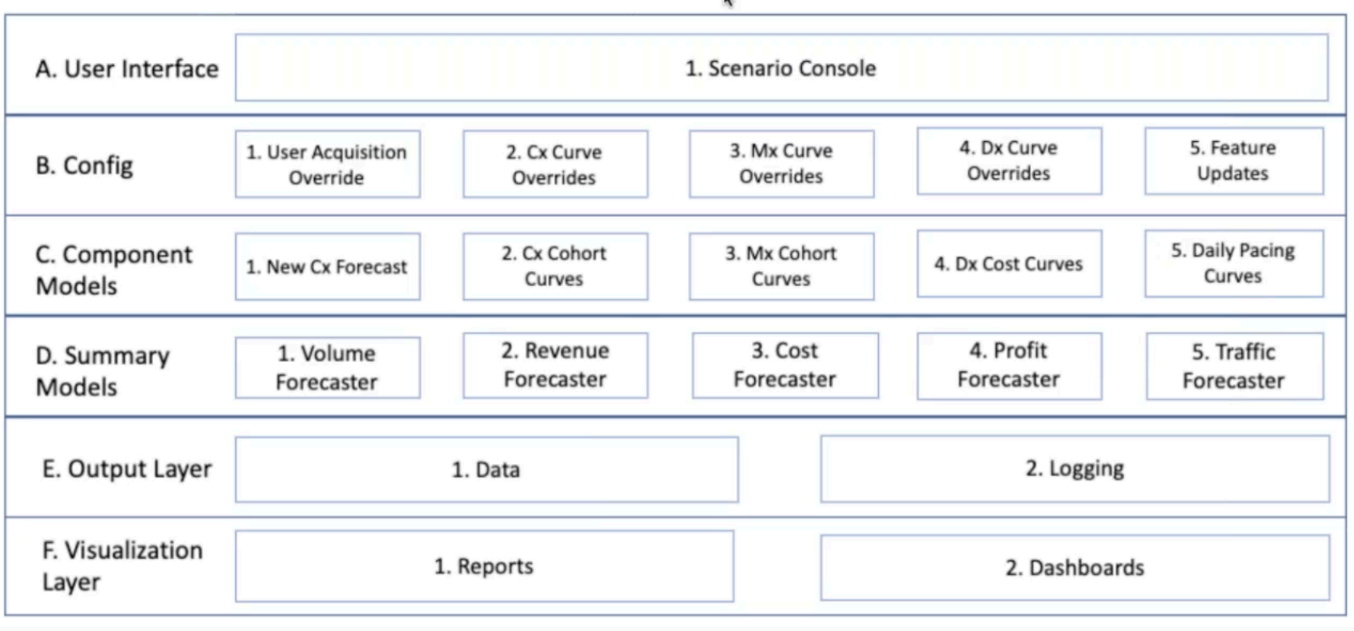
Problem

- We have a number of levers we can pull to effect company metrics such as orders, revenue, profit, e.g.
  - Supply levels
  - Demand levels
  - Fulfillment conditions
  - Marketing spend
- At annual planning level we would like to simulate different interventions to accurately estimate the impact on company metrics to make better decisions

Solution

- We build an ML based self-service application that can simulate the long term impact of any strategic action on all of DoorDash's major metrics
- One-stop shop for sizing and costing future initiatives and drastically reduces the time it takes to make decision by consolidating different aspects of planning by different teams.
- Two advantages:
  - Output is very rich as it allows for multiple cuts (e.g. geographically, by business vertical, by use cohort)
  - The structure is very modular which allows for parallel iterations and performance check points

Model Architecture



Organizing Demand Forecast

Democratization / Platformization