

Achieving personalization with LSTMs

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The Uber logo, consisting of the word "UBER" in a bold, black, sans-serif font, centered within a white square. The square is positioned in the bottom right corner of the slide, overlapping a blue decorative pattern.

UBER

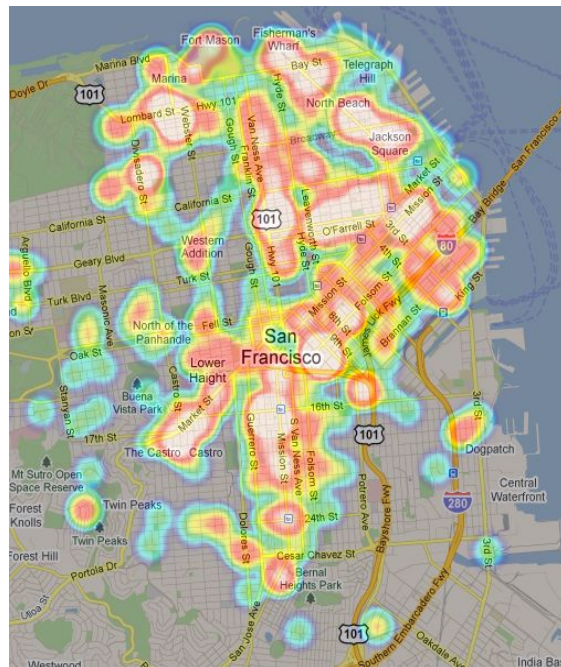
Uber heavily leverages ML for our business strategy and finance operations

Agenda

- Forecasting@Uber
- Problem Formulation
- Modeling
- Results

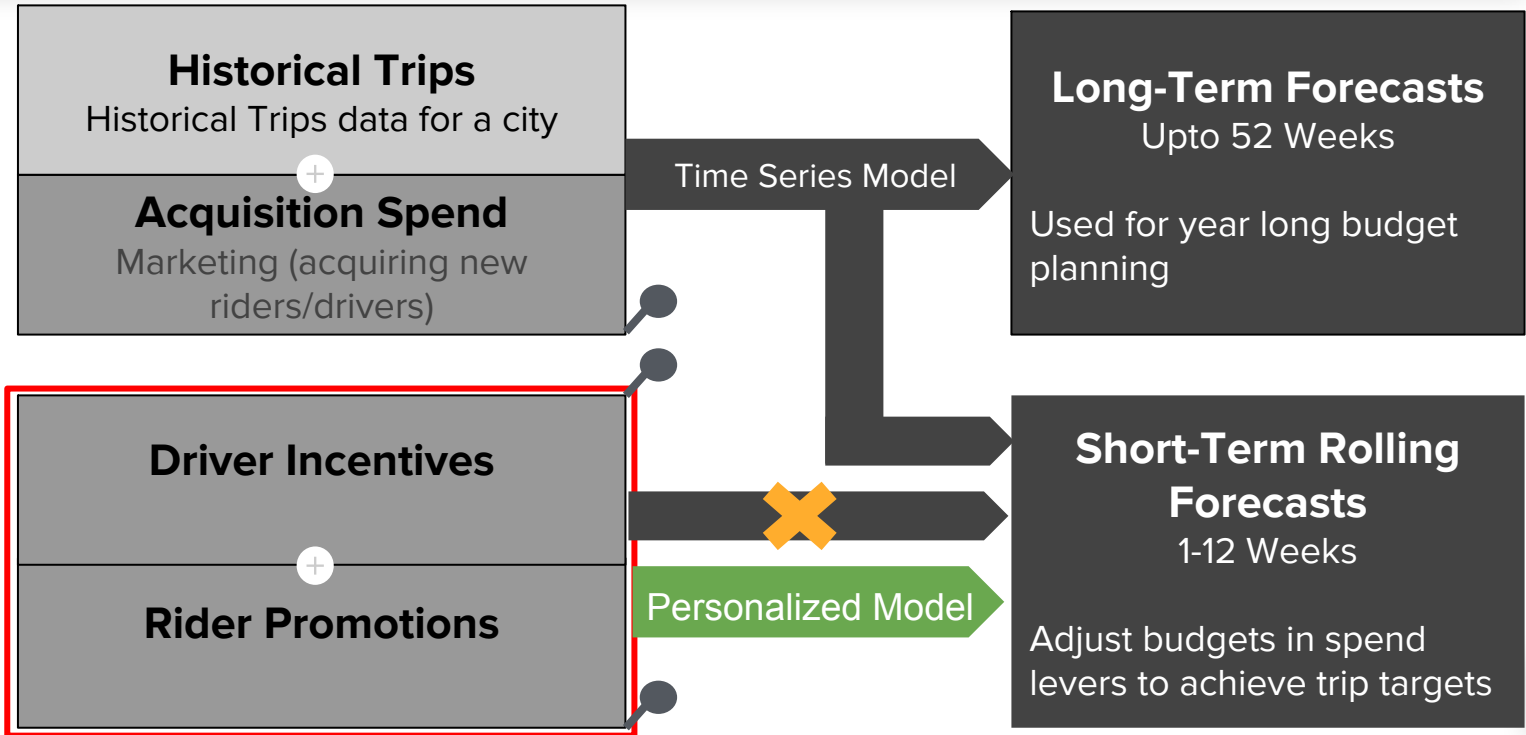
Forecasting@Uber


- Forecasting trips, gross bookings etc. are paramount to Uber
- **Time Horizon:**
 - Time horizon for forecasting varies from few minutes to a year depending on the application
- **Space:**
 - City
 - Neighborhood
 - Country etc.



Map Data@2018 Google at Uber

Trip Forecasting@Uber Finance

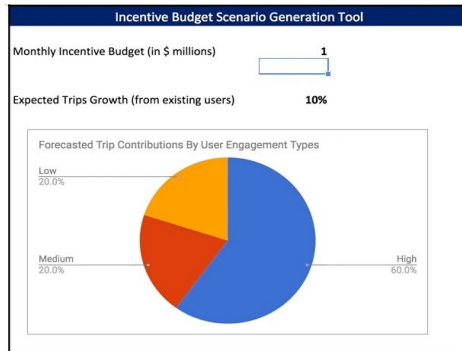


 - Represents a spending lever

Business Requirements

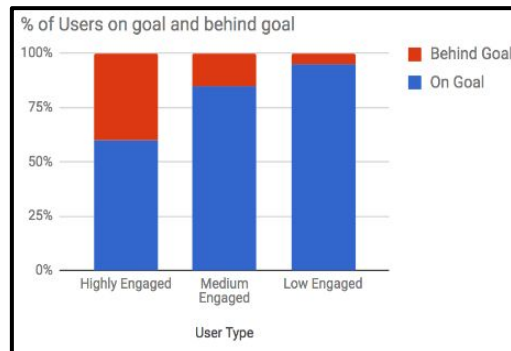
Scenario Generation

Weekly/monthly Incentive planning integrated with trip forecasting



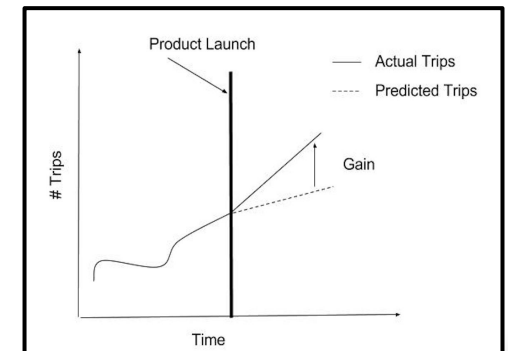
Deviation from Forecast

Which subset of users should we focus on to meet goal?



Impact of Product Launches

Quantifiable uplift in business after a product launch through counterfactuals



Combining insights like these can help Uber adjust its budget in the short term.

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Problem Formulation (Incentives)

Functional Form

Learn a function g to establish the following relationship

$$g(\mathbf{I}, f_t, Trips_t) = \mathbf{T}$$

Where,

f_t = vector of features from 0 to current time t

$Trips_t$ = vector of trips from 0 to current time t

\mathbf{I} = Budgeted incentive spend vector for next N weeks

\mathbf{T} = Forecasted trips vector for next N weeks

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Data (Feature Vector)

Feature Type	Driver Features
Static	City, Acquisition channel, Acquired month etc.
Behavioral	Trips, Supply hours, Open Supply Hours, Accepts, Rejects, Cancellations, Earnings, Referrals, %Surge Trips etc.
Incentives	<ul style="list-style-type: none">● Incentive features like DxGy, Guaranteed Surge etc.● Look ahead features of budgeted incentives for the future

Data Granularity: Each row of data set corresponds to weekly features of a driver and N target variables (one for each of future weeks)

Modeling Parameters

Parameters	Value
Model Granularity	Separate model for each city
Evaluation Metric	Mean Absolute Error (MAE) of each driver for week 1-N MAPE at City level to check model if the model is unbiased
Baseline	Driver - use last week's trips as prediction for next 1-N weeks
Best Model	LSTMs with Zero Inflated Poisson Loss

LSTMs vs Classical ML Models

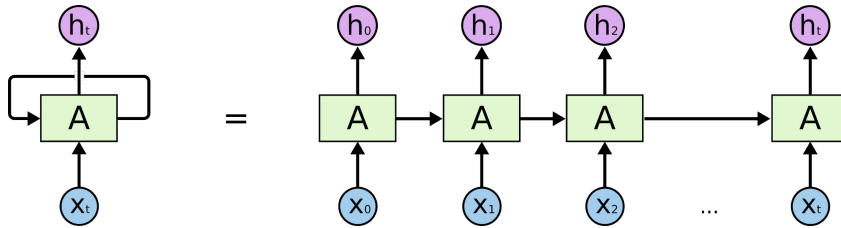


Fig: An unrolled recurrent neural network

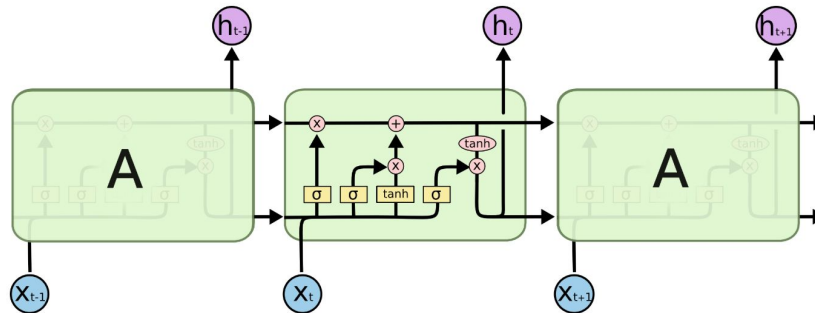


Fig: Repeating Module of LSTM

- The abundance of Uber's data serves very well for training data hungry deep learning models like LSTMs
- Time dependencies are well captured
- LSTMs model hidden non-linear interactions

Zero Inflated Poisson (ZIP) Loss

Weekly trips distribution (i.e., the y variable) has the following properties:

- Non-negativity: Trips is a count data
- Lots of structural zeros in the system

Hence zero-inflated-poisson (ZIP):

$$\mathbb{P}(y = 0) = \pi + (1 - \pi)e^{-\lambda}$$

$$\mathbb{P}(y = h) = (1 - \pi) \frac{\lambda^h e^{-\lambda}}{h!}, h \geq 1$$

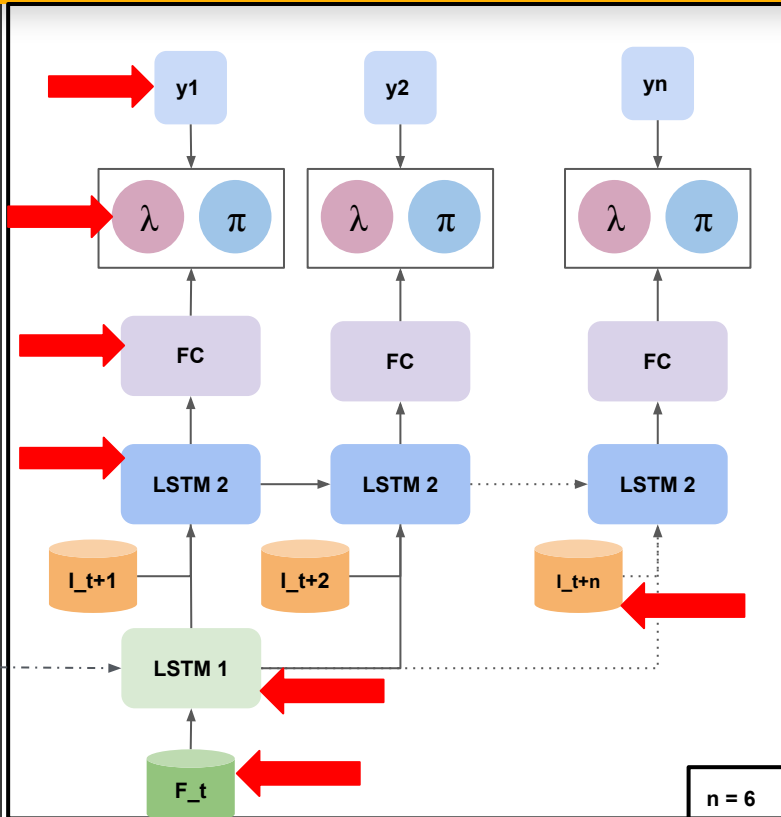
Where,

λ is the expected Poisson count for the individual;

π is the probability of extra zeros



LSTM Model Architecture

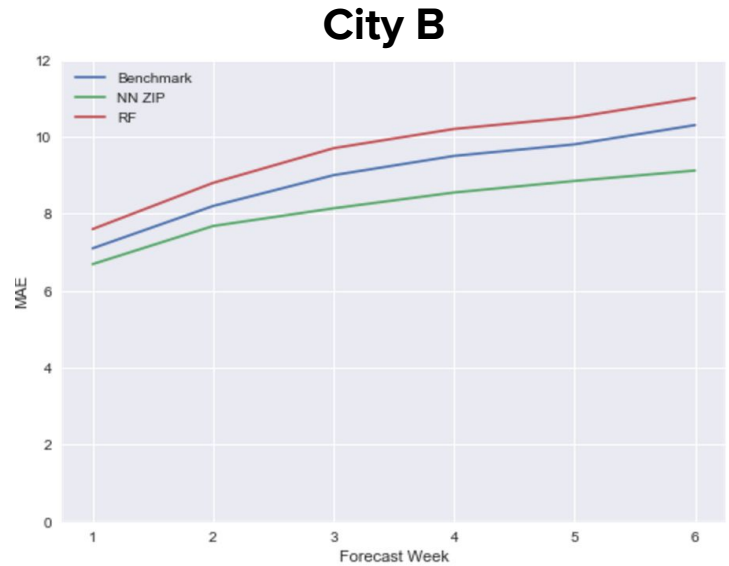
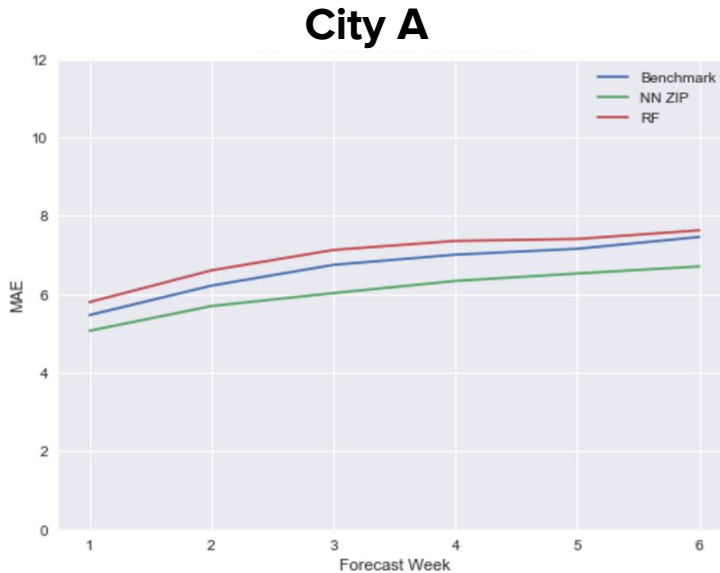


Variable	Description
F_t	Static, behavioral features at time t for a driver
LSTM 1	Output: Feature embeddings per driver
LSTM 2	Input: Feature embeddings and future incentives ($I_{t+1} \dots I_{t+12}$) Output: Updated feature embeddings at a given forecasting period
Lambda, Pi	Parameters of ZIP distribution per driver per week
FC	Fully connected layer to map the feature embeddings to two outputs
$y_1 \dots y_n$	Final trip predictions as expectation of ZIP

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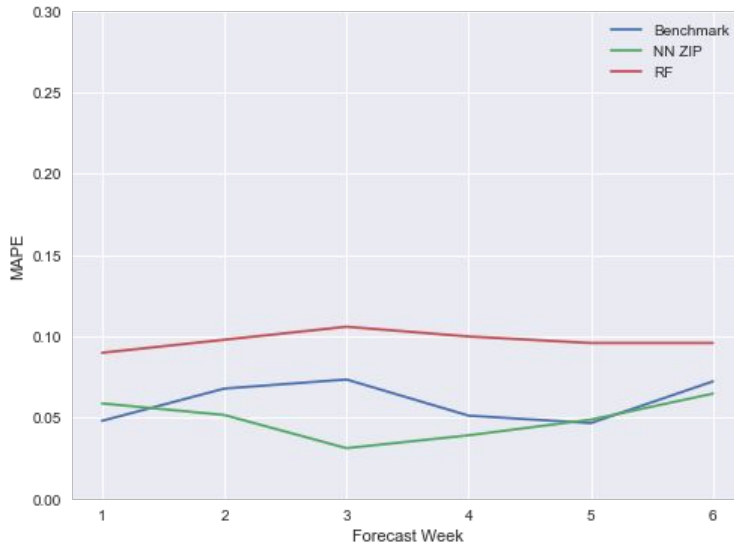
Mean Absolute Error (MAE) Comparison



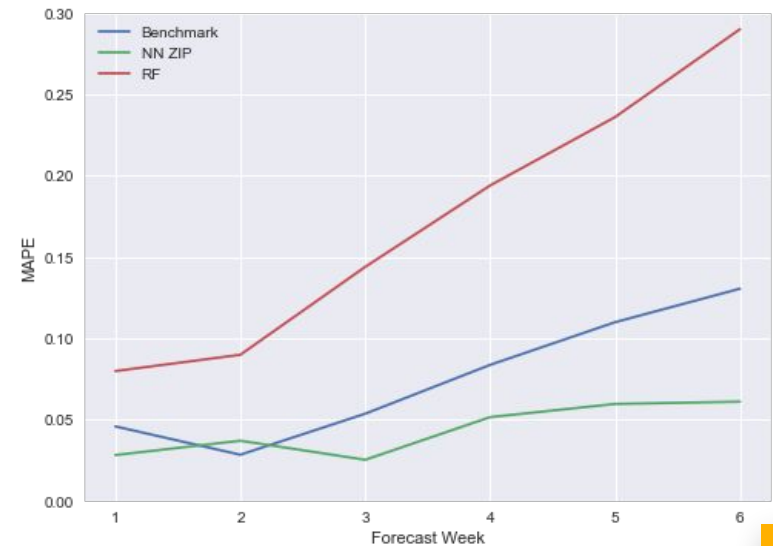
LSTM ZIP outperforms the basic models (~30% improvement)

Mean Absolute Percentage Error (MAPE)

City A

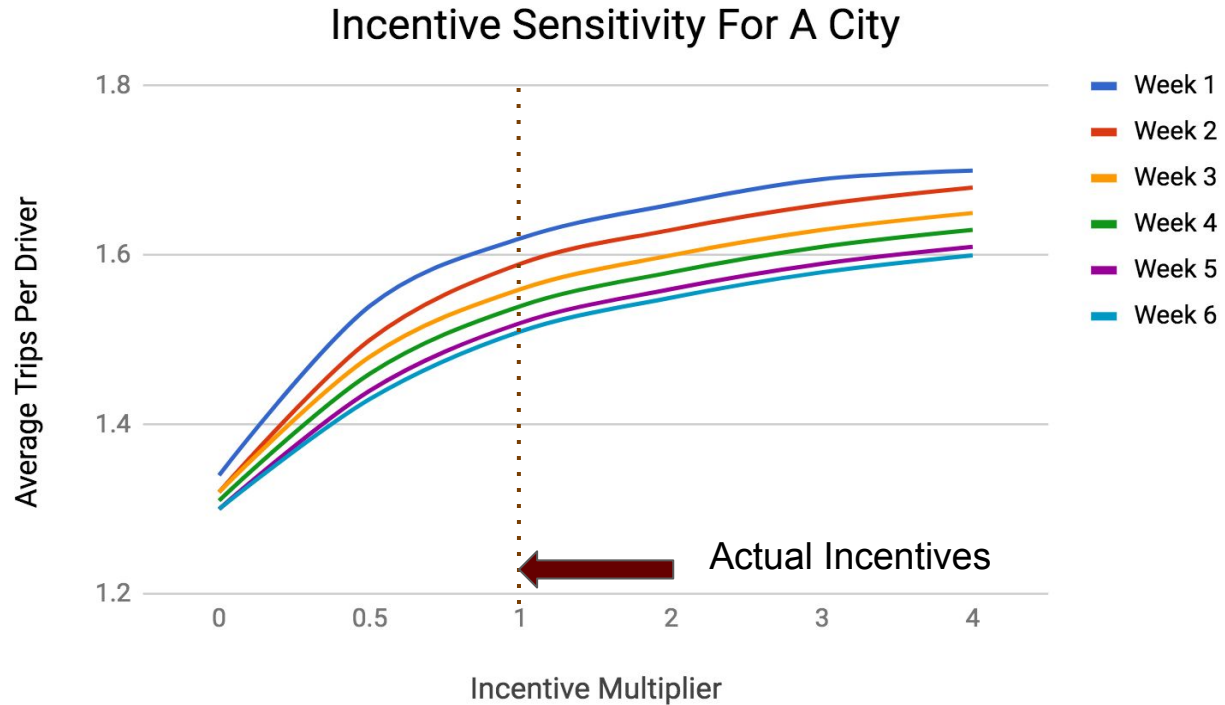


City B



MAPE is similar to the benchmark indicating Neural Network model is not biased

Incentive Sensitivity Curves



*Note that values are rescaled

Thank you

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Data Scientists

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UBER

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