



Travel better together



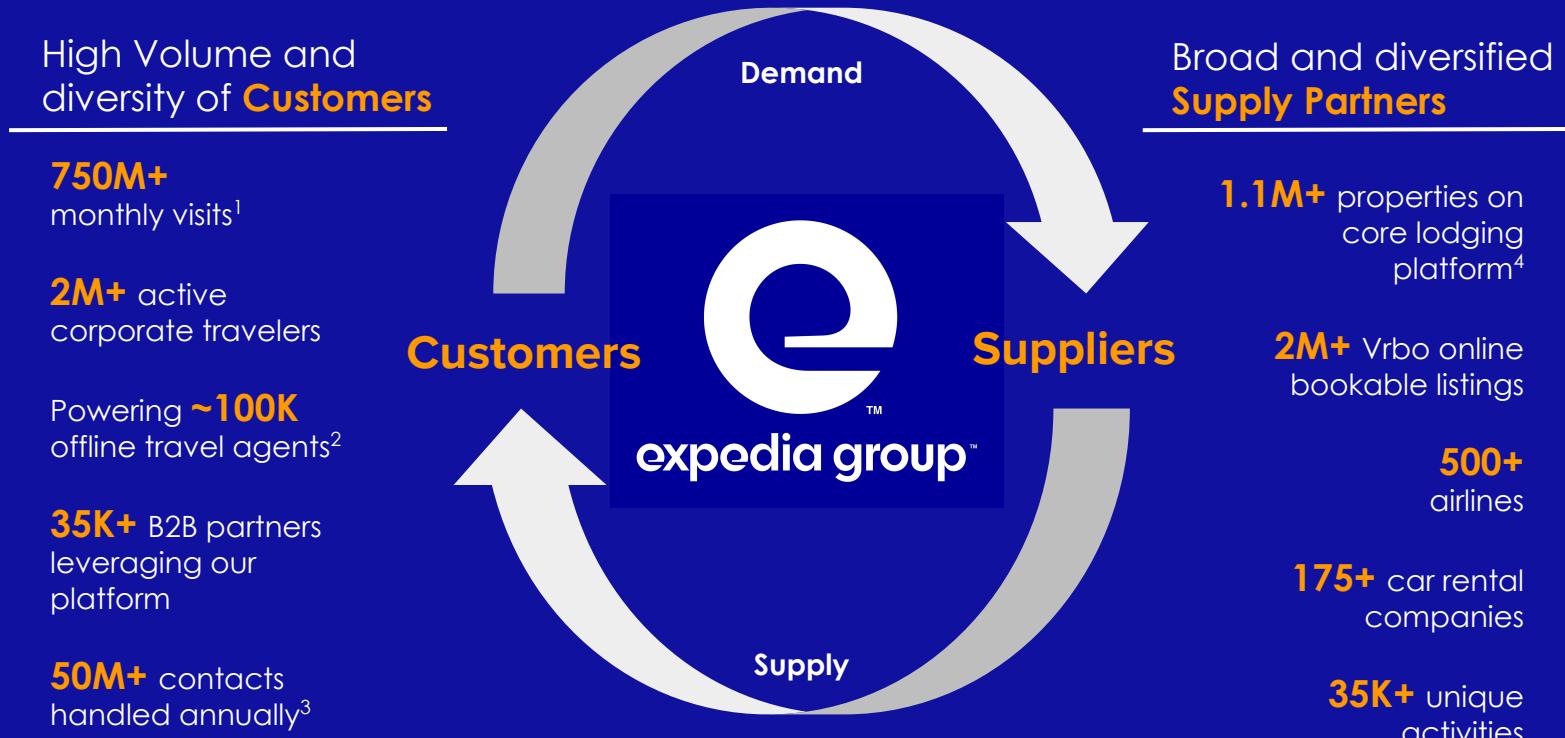
Deep Personalized Retargeting

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Vrbo, Part of Expedia Group, Austin, Texas and London, UK**

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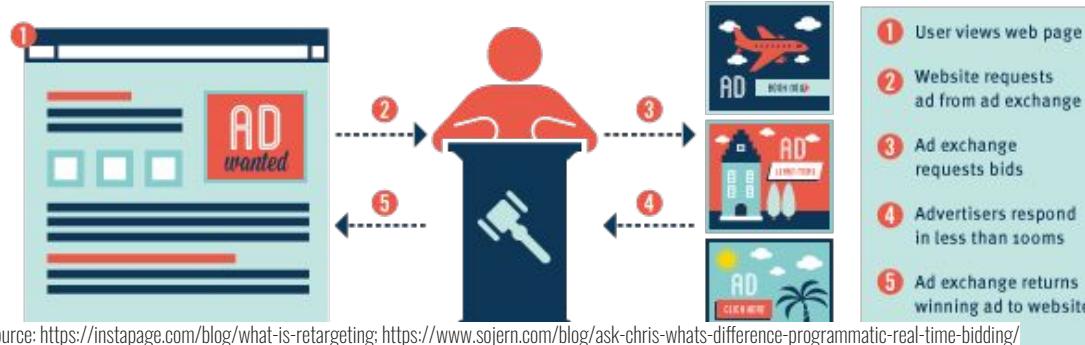
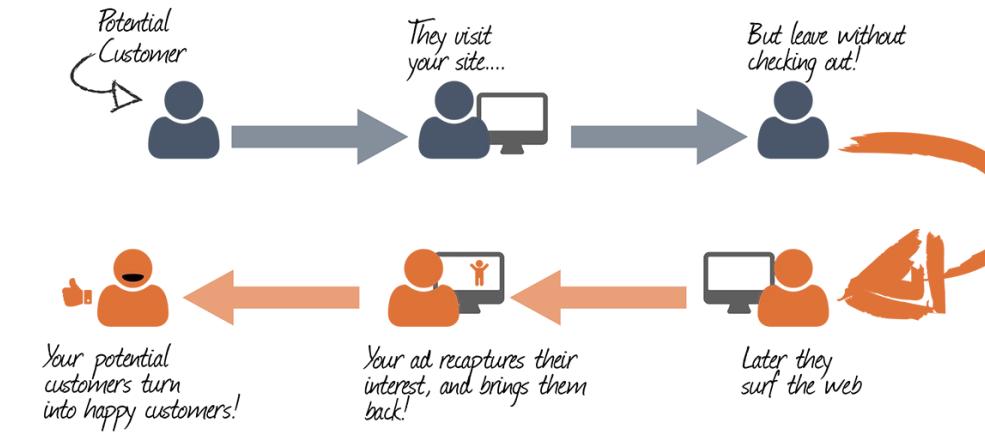


Largest Travel Platform in the World ...

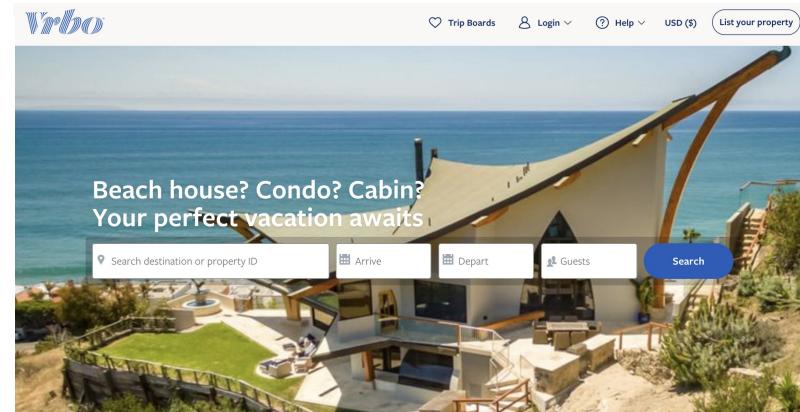
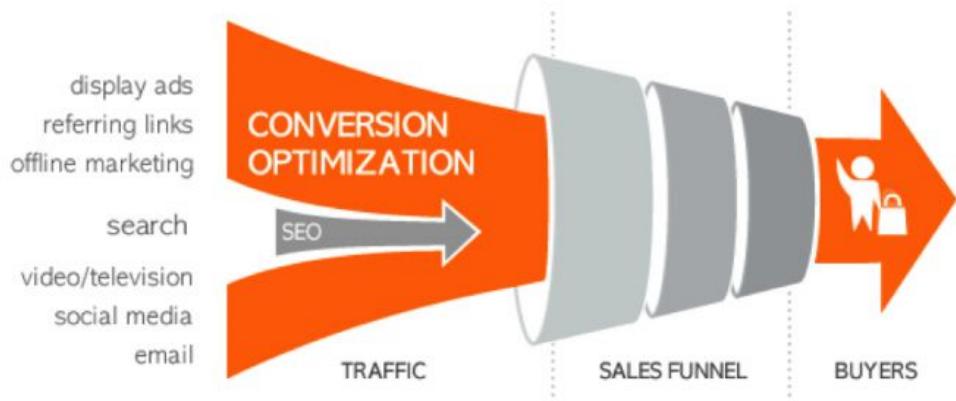


Notes: Expedia Group data shown as of 3/31/19, unless otherwise noted. 1. Monthly visits based on data for Brand Expedia, Hotels.com, Orbitz, Travelocity, Wotif, Vrbo, trivago and Hotwire combined during 2018. 2. Offline travel agents based on number of sales agents in Global Customer Operations, Expedia Partner Solutions (EPS), Vrbo, Classic Vacations, CruiseShipCenters, Travel Agent Affiliate Program (TAAP). 3. Contacts handled annually include calls, emails, chats and social media. 4. Includes more than 460,000 integrated Vrbo listings. This information is based on Q2 19' Earning Report.

Retargeting and Real Time Bidding



Short-term Vacation Rental Two-sided Marketplace Platforms



Your vacation is safe with us
Secure payments, 24/7 support and
a Book with Confidence guarantee



Better vacations start here
From booking to staying, the whole
process is easy and enjoyable



All the comforts of home
Enjoy full kitchens, laundry, pools,
yards and more



More for less
More space, more privacy, more
amenities — more value

Research Questions

- How to predict conversion probability and value for real time bidding?
- How to improve the prediction of conversion probability and value?
- How to automatically extract features and account for unobservable features?
- How to productionalize such system?
- How is the performance of the designed system compared with alternatives?

Real time bidding use case in Vrbo

Google

vacation rental in vancouver

Search

All Maps News Images Shopping More Settings Tools

About 132,000,000 results (0.74 seconds)

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What is the best area to stay when traveling to Vancouver? Downtown: 375 vacation rentals. Kitsilano: 186 vacation rentals. West Side: 737 vacation rentals. East Side: 676 vacation rentals. City Centre: 348 vacation rentals.

Downtown - Stanley Park - Kitsilano 186 vacation rentals - West Vancouver

Vrbo

Trip Boards Login Help USD (\$) List your property



Vancouver

We found 1,263 vacation rentals — enter your dates for availability

Where Vancouver, BC, Canada Dates Guests Search

Top destination with US travelers

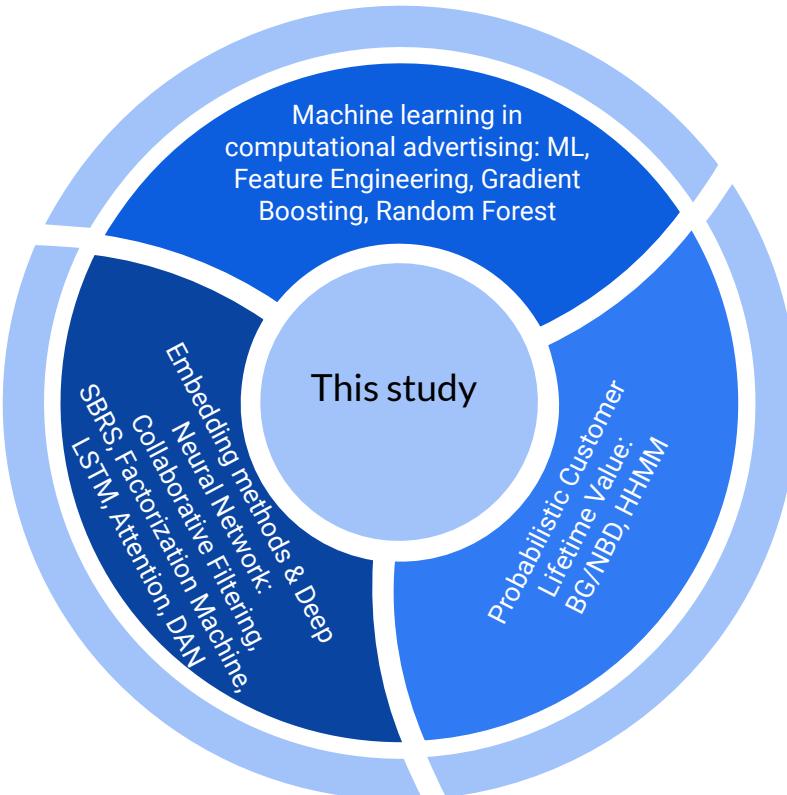
Home > Canada > British Columbia > Greater Vancouver > Vancouver

Book soon! 1,155 people are looking at Vancouver rentals.

Discover your favorite property type



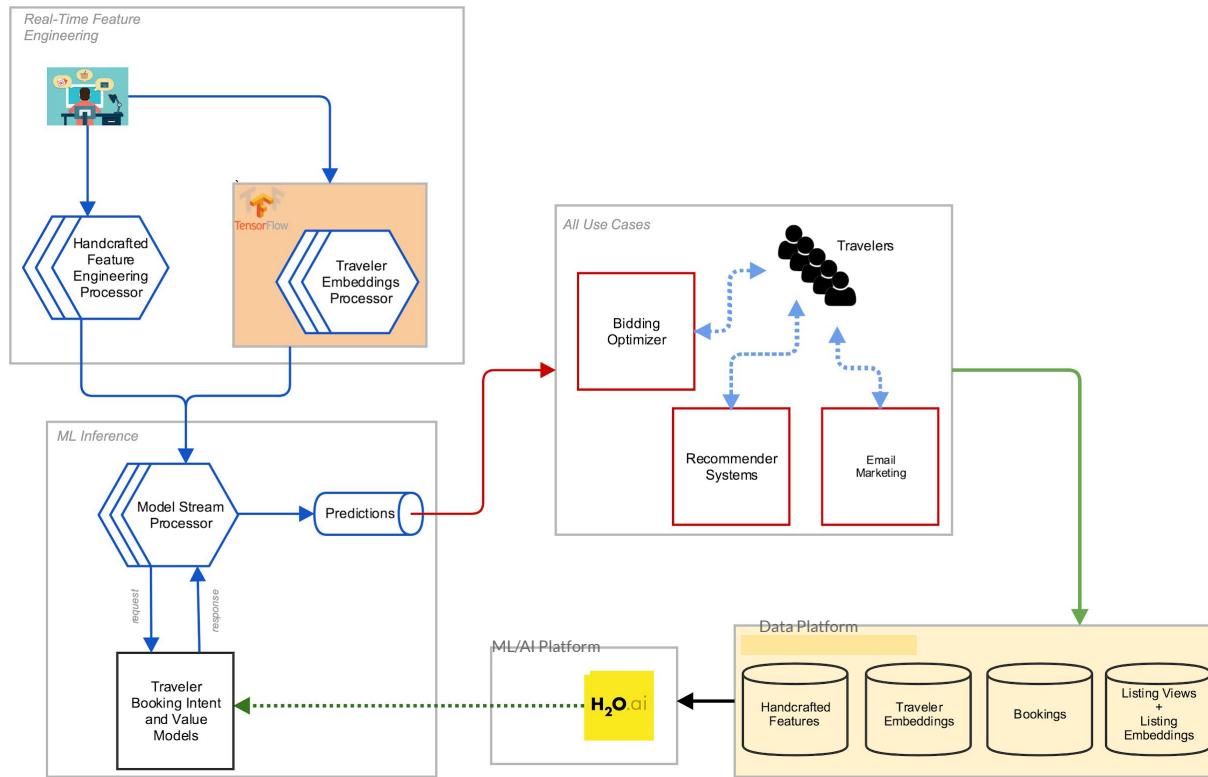
Position of this research in literature



This study in the context of literature

- Leverage embeddings to improve the intent prediction solution
- Extend embedding features from linear to non-linear
- Sweet spot with low cost and high value for combining deep neural networks with shallow neural networks and tree-based method
- We deployed our solution into a production system

Overview of the System



Overview of the Methodology

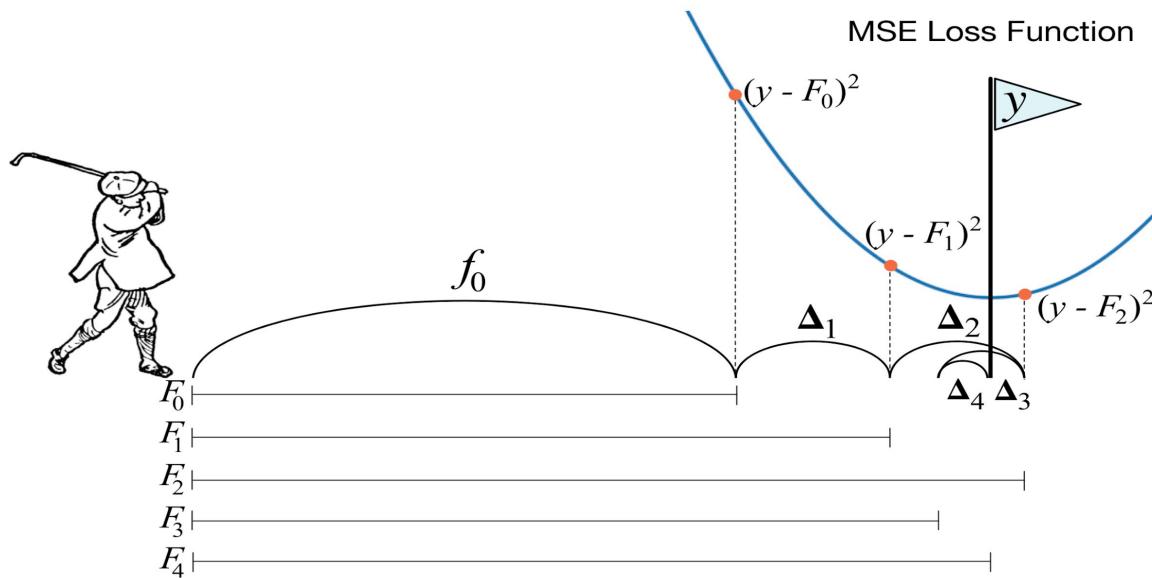
- Internal anonymized clickstream data is collected for millions of users from two different seven-day periods:
 - The 1st dataset was used to generate embeddings using Deep Average Network and the LSTM with Attention
 - The 2nd dataset was used to evaluate the learned embeddings on the Traveler Booking Intent Model
- Three baselines methods:
 - Random Listing Embedding Selection
 - Averaging Embeddings
 - LSTM with Attention

Overview of Results

Algorithm	AUC	Precision	Recall	F1-Score
Random	0.973	0.821	0.633	0.715
Averaging Embeddings	0.971	0.816	0.628	0.71
LSTM + Attention	0.976	0.877	0.62	0.727
DAN	0.978	0.888	0.628	0.735

Settings	AUC	Precision	Recall	F1-Score
Only handcrafted Feat.	0.975	0.817	0.651	0.724
Handcrafted + DAN Feat.	0.978	0.888	0.628	0.735

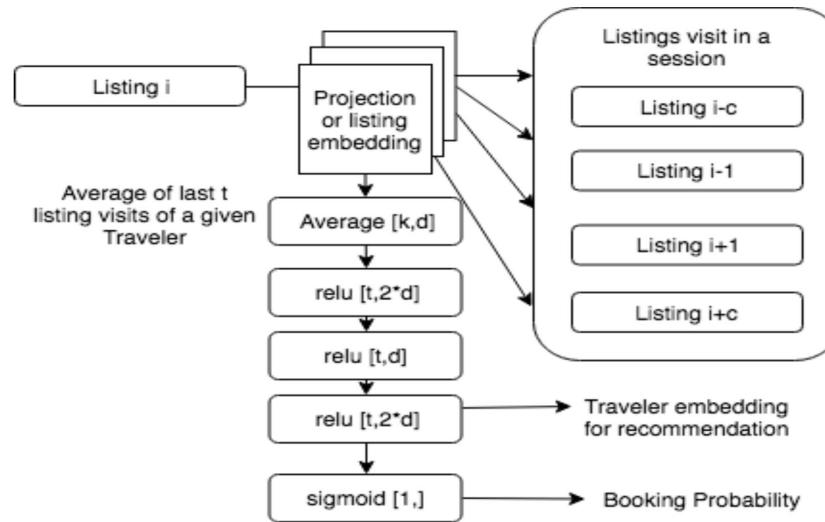
Model -1



$$\hat{y}_j \equiv F(\mathbf{x}_j) = \sum_{k=1}^K f_k(x_i), \text{ where } f_k \in \mathbb{F}$$
$$L^{(t)} = \sum_j l(y_j, \hat{y}_j^{(t-1)} + f_t(\mathbf{x}_j)) + \Omega(f_t)$$

Source: <https://explained.ai/gradient-boosting/>

Model - 2



$$\frac{1}{S} \sum_{s=1}^S \sum_{-c \leq i \leq c, i \neq 0} \log p(l_{i+j} | l_i), \text{ where } p(l_{i+j} | l_i) = \frac{\exp(\nu_{l_{i+j}}^T \nu_{l_i})}{\sum_{l=1}^L \exp(\nu_l^T \nu_{l_i})}$$

However, by negative sampling $p(l_{i+j} | l_i) = \frac{\exp(\nu_{l_{i+j}}^T \nu_{l_i})}{1 + \exp(\nu_{l_{i+j}}^T \nu_{l_i})}$

Model - 3

- Target to predict: $P(Y_j|S_j, C_j) = \text{sigmoid}(f(\nu_j.))$
- Encoder-Decoder Architecture (Deep Average Network - DAN):

$$f(\nu_j.) = \text{relu}(\omega_1 \cdot h_2(\nu_j.) + \beta_1)$$

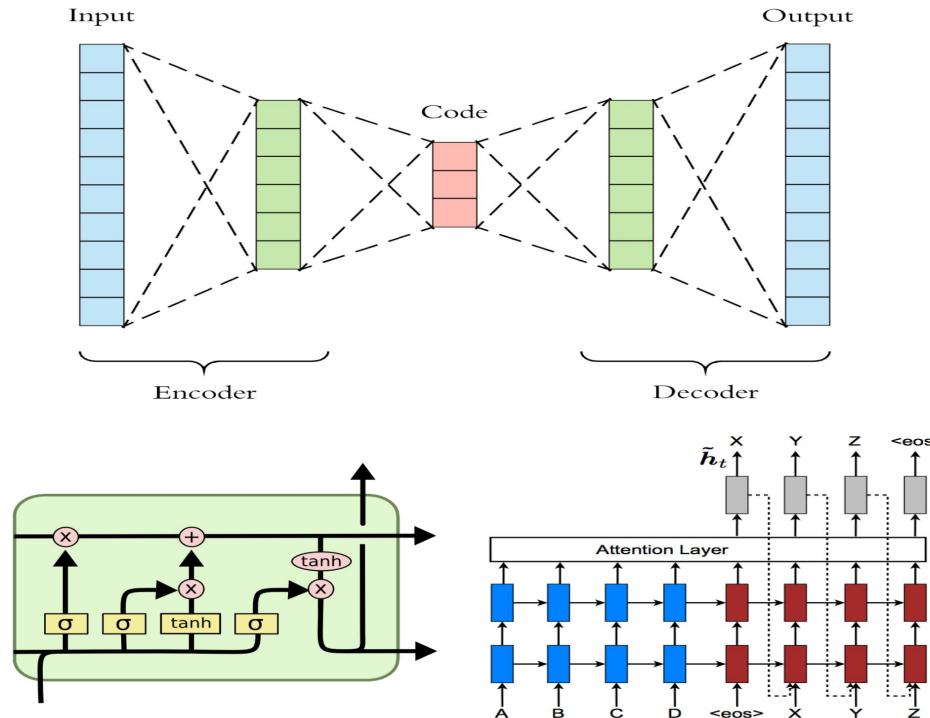
$$h_1(\nu_j.) = \text{relu}(\omega_2 \cdot h_1(\nu_j.) + \beta_2)$$

$$h_2(\nu_j.) = \text{relu}(\omega_3 \cdot \frac{1}{k} \sum_{i=1}^t \nu_{ji}) + \beta_3)$$

LSTM Architecture: $f(\nu_j^t) = \text{sigmoid}(\omega_f[h_t, \nu_j^t] + \beta_f) \cdot f(\nu_j^{t-1})$
 $+ \text{sigmoid}(\omega_i[h_t, \nu_j^t] + \beta_i) \cdot \tanh(\omega_c[h_{t-1}, \nu_j^t] + \beta_c)$

- LSTM + Attention: $f(\nu_i) = \text{softmax}(\omega^T \cdot h_T) \tanh(h_T)$

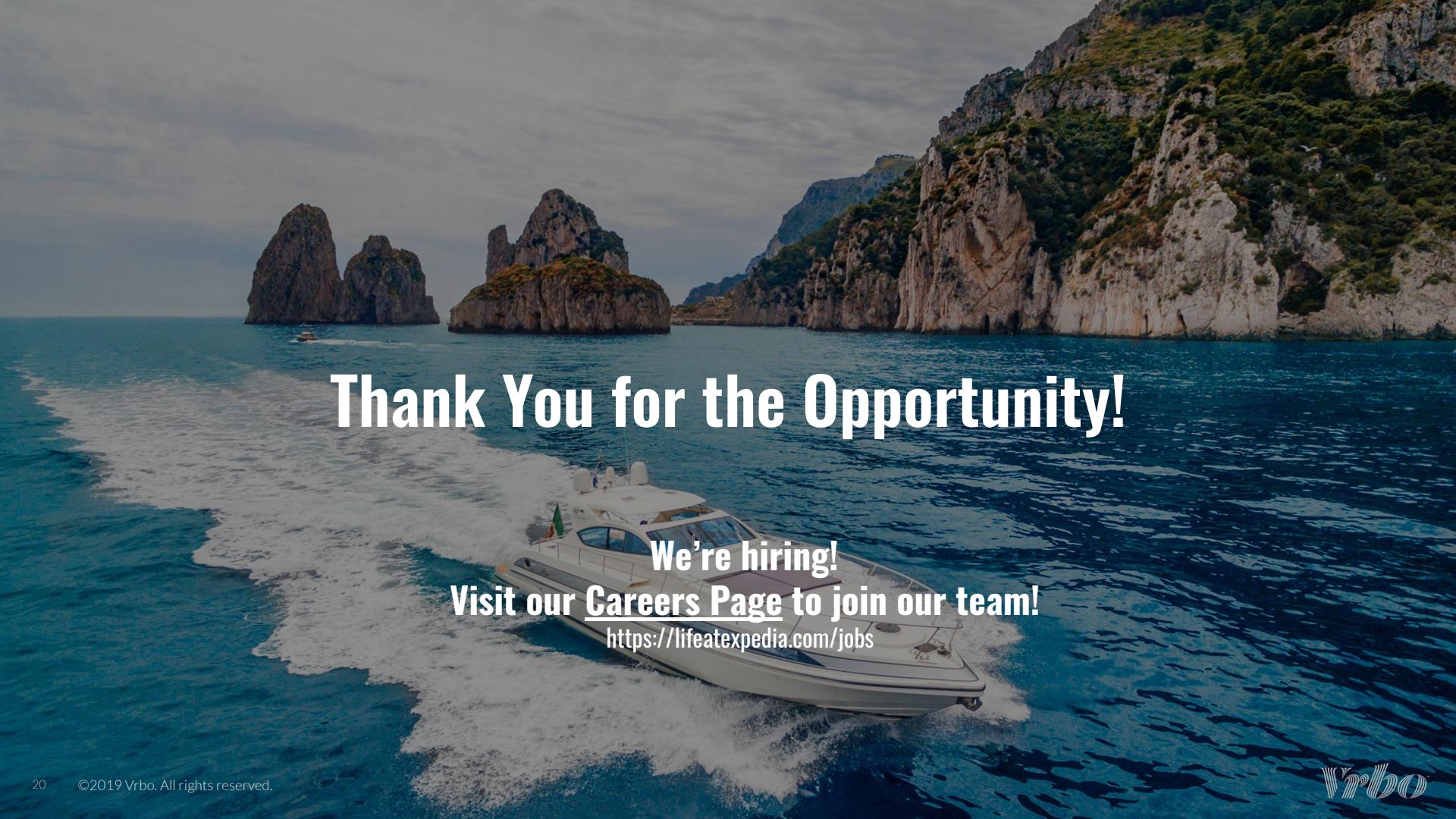
LSTM, Attention, and Encoder-Decoder Network Architecture



Conclusion

- Proposed a hybrid deep learning framework for a massive vacation rental marketplace.
- Deployed end-to-end manner and leveraged for re-targeting.
- Combined shallow and deep neural network network embedding for listing and traveler embedding and tree based boosting methods.
- Extension by incorporating more contextual spatio-temporal information in the model.
- Full paper proceeding of ASONAM IEEE/ACM conference can be found [here](#).

Q&A



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