B2B Advertising: Joint Dynamic Scoring of Account and Users

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Business to Business (B2B) Marketing

Business to Consumer (B2C) Marketing attracts headlines in advertising research.

Unlike B2C, B2B marketing focuses on suppliers selling products and services to other businesses.
e.g., software systems, engines to airplane manufacturers

In B2B,
An **account** is a business buyer, prospective or existing

Each account comprises individuals, called **leads**

Leads interact with potential suppliers' website or through other channels, increasingly digital

The buying cycle is long: 6 to 18 months or more

The Account's decision whether to buy is a consultative decision among the Leads
- group decision making

B2B’s contribution to the Web’s success

“[t]he global B2B eCommerce market **valuing** USD 12.2 trillion in 2019 is over 6 times that of the B2C market" (https://www.statista.com/study/44442/statista-report-b2b-e-commerce/)

B2B’s digital marketing **growth** is at par with that of the more commonly studied B2C setting. (https://cmosurvey.org/wp-content/uploads/2019/08/The_CMO_Survey-Highlightsand_Insights_Report-Aug-2019-1.pdf, pp. 20)

Use Cases

Customer Acquisition

Retention of Customers

Cross Selling

Funnel Leakage

Optimal Allocation of Resources

Rule based scoring

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AI driven scoring

B2B: Research Setting

(a) the group collaboratively decides whether to buy and the decision is dynamic;

(b) differences exist among the individuals' interactions with the supplier;

(c) over the long purchase cycle, depending on scoring the group dynamics, the supplier engages with the individuals, including allocating costly human salespersons toward some individuals, but not toward all individuals in the group.

B2B: Research Questions

How to Jointly Score

(a) Collaborative group decision only from activity data of individual members of the group, without any data of consultations among individual members.

(b) Dynamics of the group's decision

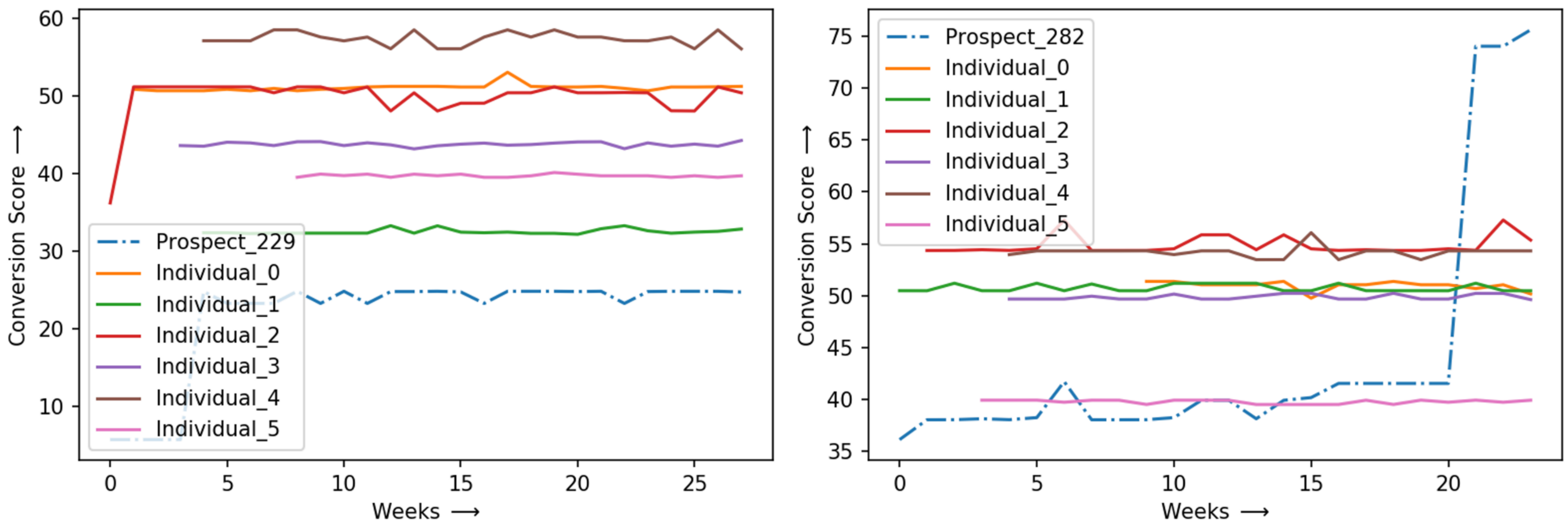
(c) Dynamics of each individual in the group for differently allocating resources to them at different time periods.

Data

Types of Information	Features / Variables
Dynamic Activities of Individuals	*open email, click email, send email,* unsubscribe email, open sales email, click sales email, send sales email, forwarded email received, forwarded email sent
Static Features of Individuals	source of arrival, opt out of email, opt out of phone
Static Features of accounts	revenue, number of employees

Table 1: Data Description: Data of 9 activities over 8 months for each individual. The top 3 activities are *italicized*. The second row shows 3 categorical static features, vary by individuals. The third row shows group level two static features, they do not vary across individuals within the group; vary by groups.

Joint Scoring – Group (Account) and Individuals (Users, Leads)



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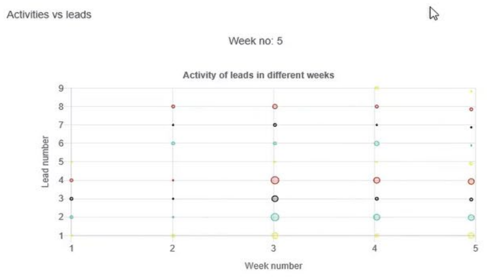
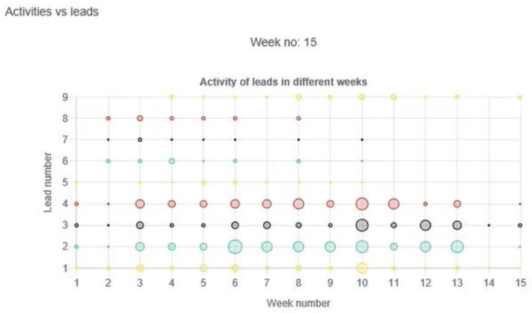
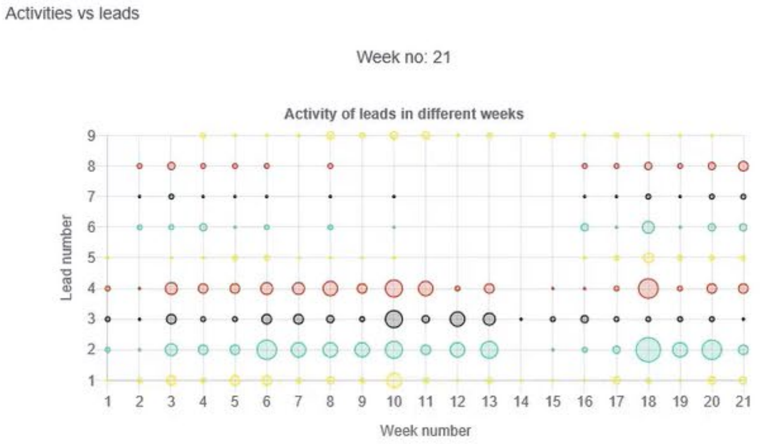
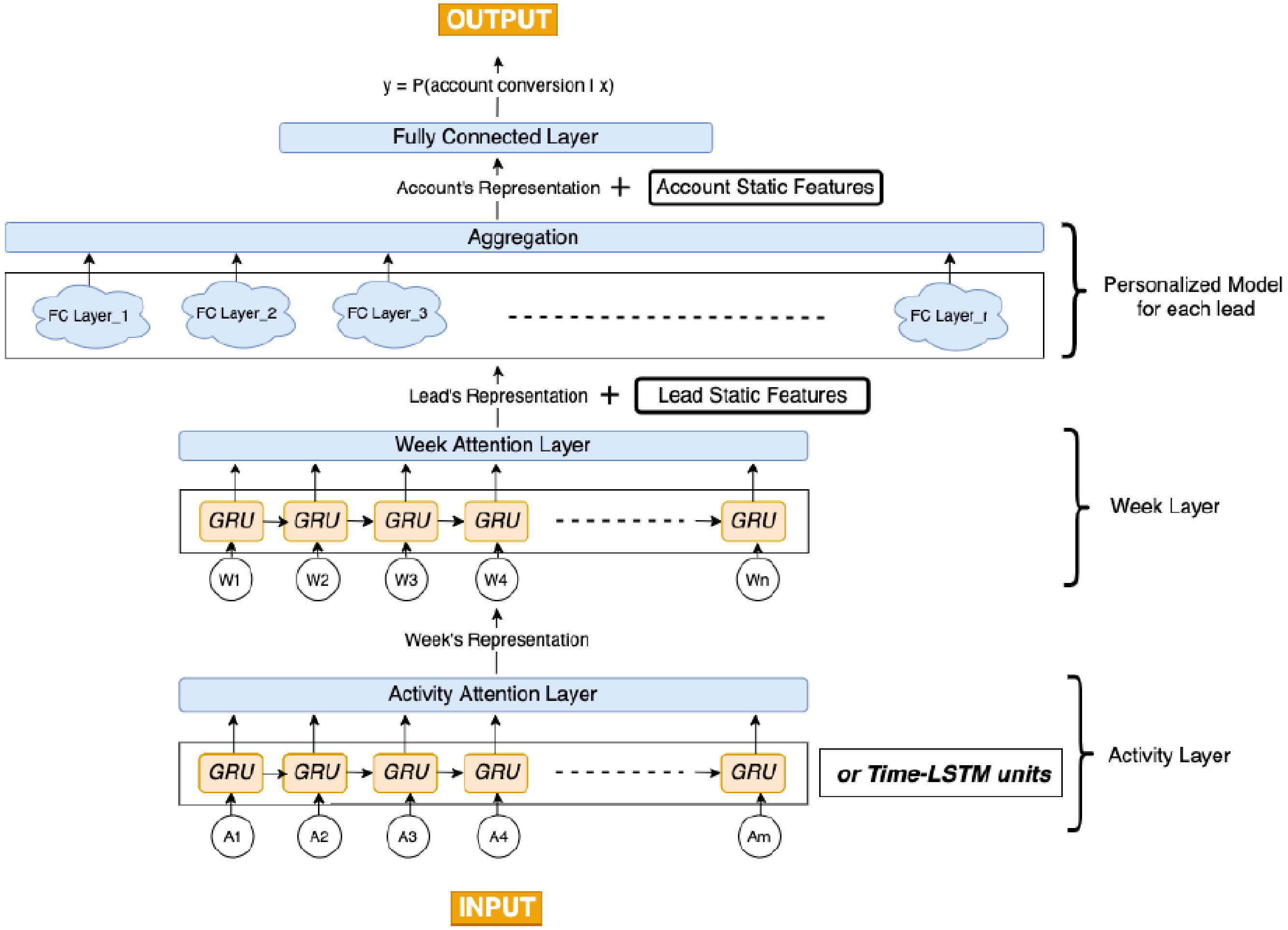
Dynamic, Snapshots – Group Scoring vs. Individuals’ Activities







Architecture 1 (HAN)[1] : Sequence of Activities



1. Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. 2016. Hierarchical attention networks for document classification. In Proceedings of the 2016 conference of the North American chapter of the association for computational linguistics: human language technologies.1480–1489.
2. Cheng, L., Guo, R., Silva, Y., Hall, D., & Liu, H. (2019, May). Hierarchical attention networks for cyberbullying detection on the instagram social network. In *Proceedings of the 2019 SIAM International Conference on Data Mining* (pp. 235-243). Society for Industrial and Applied Mathematics.

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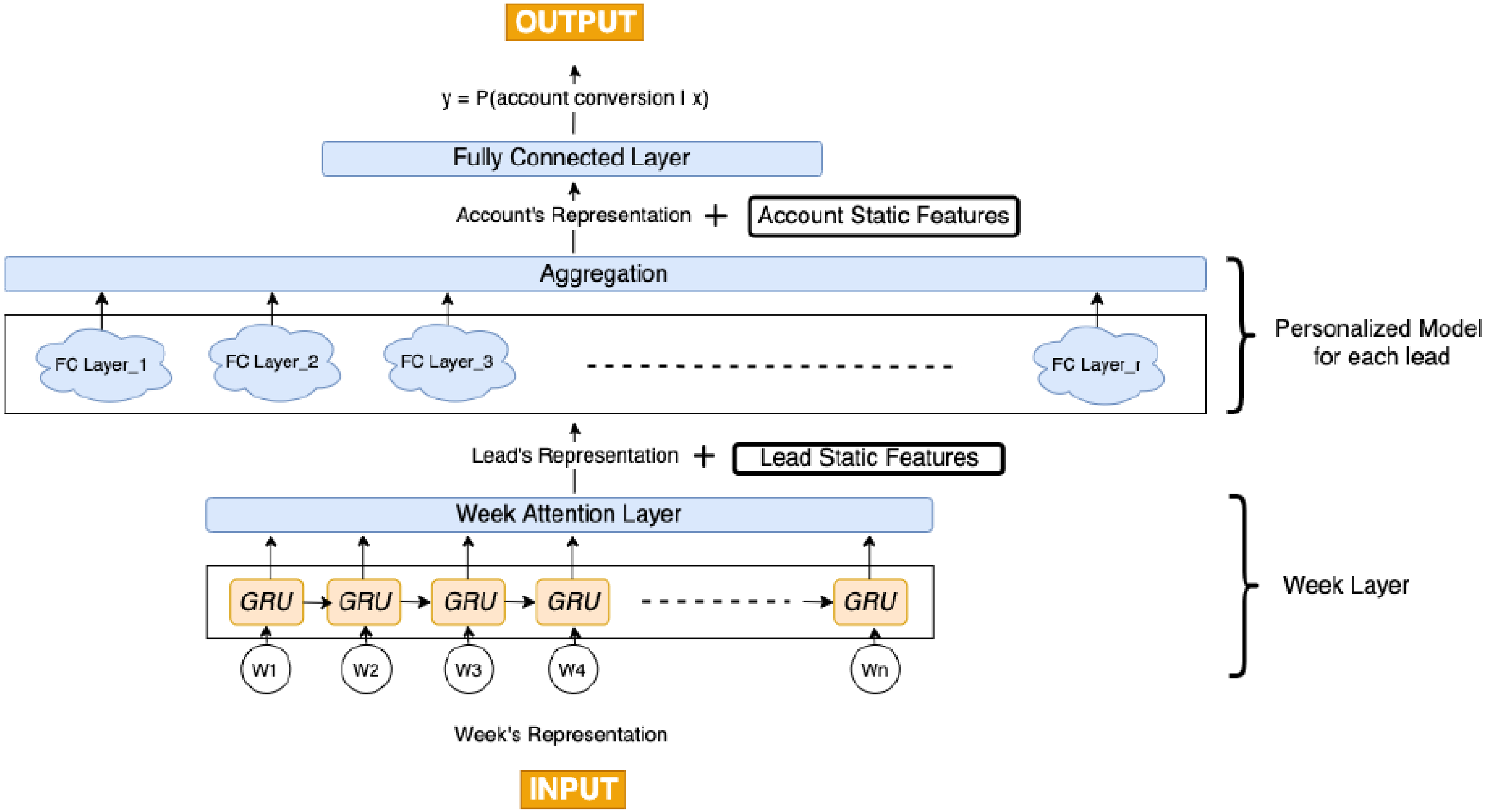
Architecture 2: Frequency of Activities



1. Cheng, L., Guo, R., Silva, Y., Hall, D., & Liu, H. (2019, May). Hierarchical attention networks for cyberbullying detection on the instagram social network. In *Proceedings of the 2019 SIAM International Conference on Data Mining* (pp. 235-243). Society for Industrial and Applied Mathematics.
2. Zhu, Y., Li, H., Liao, Y., Wang, B., Guan, Z., Liu, H., & Cai, D. (2017, August). What to Do Next: Modeling User Behaviors by Time-LSTM. In *IJCAI* (Vol. 17, pp. 3602-3608).

Results

Model	AUC
Baseline 1: Activity Sequence, Individual loss, No Aggregation	0.74
Baseline 2: Activity Frequency, Group loss, Aggregation	0.82

Table 2: Baseline Model Performance: Frequency of Activities with Aggregation performs appreciably better.

Experiments 1-6 with different aggregation methods	AUC
Neural Network methods	
1. FNN Layer	0.86
2. Many-to-One GRU	0.87
3. Many-to-Many GRU and Attention Layer	0.87
Statistical functions	
4. Maximum probability converts	0.83
5. Probability at least one individual converts	0.67
6. Geometric Mean	0.69

Table 3: Model Performance: Sequence of Activities. All proposed models 1-6 appreciably outperform the baseline-sequence model. Neural network aggregation methods perform better than use of statistical functions for aggregation.

Experiments 7-9 with time-LSTMs	AUC
7. FNN Layer	0.85
8. Many-to-One GRU	0.85
9. Many-to-Many GRU and Attention Layer	0.86

Table 4: Model Performance: Sequence of Activities, time-LSTMs. All proposed neural network models, outperform Baseline1 strongly, and Baseline 2 as well.

Conclusion

- Joint Scoring of Group Decision and Individuals’ Interests
- Without data on the group decision consultative process, only individual level data
- Using different types of aggregation to pool information across individuals
- Good performance evaluation for conversion decision
- Influence of each individual on the group decision obtainable from attention weights
    - Evaluation of influence yet to be done

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