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motion moments magic

Hyper-personalization in retail through AI and behavioral science

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Use-case: Big supermarket chain with a mobile loyalty app

Their questions:

1. How can we **increase engagement**?
2. How can we **become more relevant** and personalized?
3. How can we **reduce churn** and app-user frustration?

What they tried:

- Personalized messages based on offline segmentation
- Location based targeting
- Time based targeting

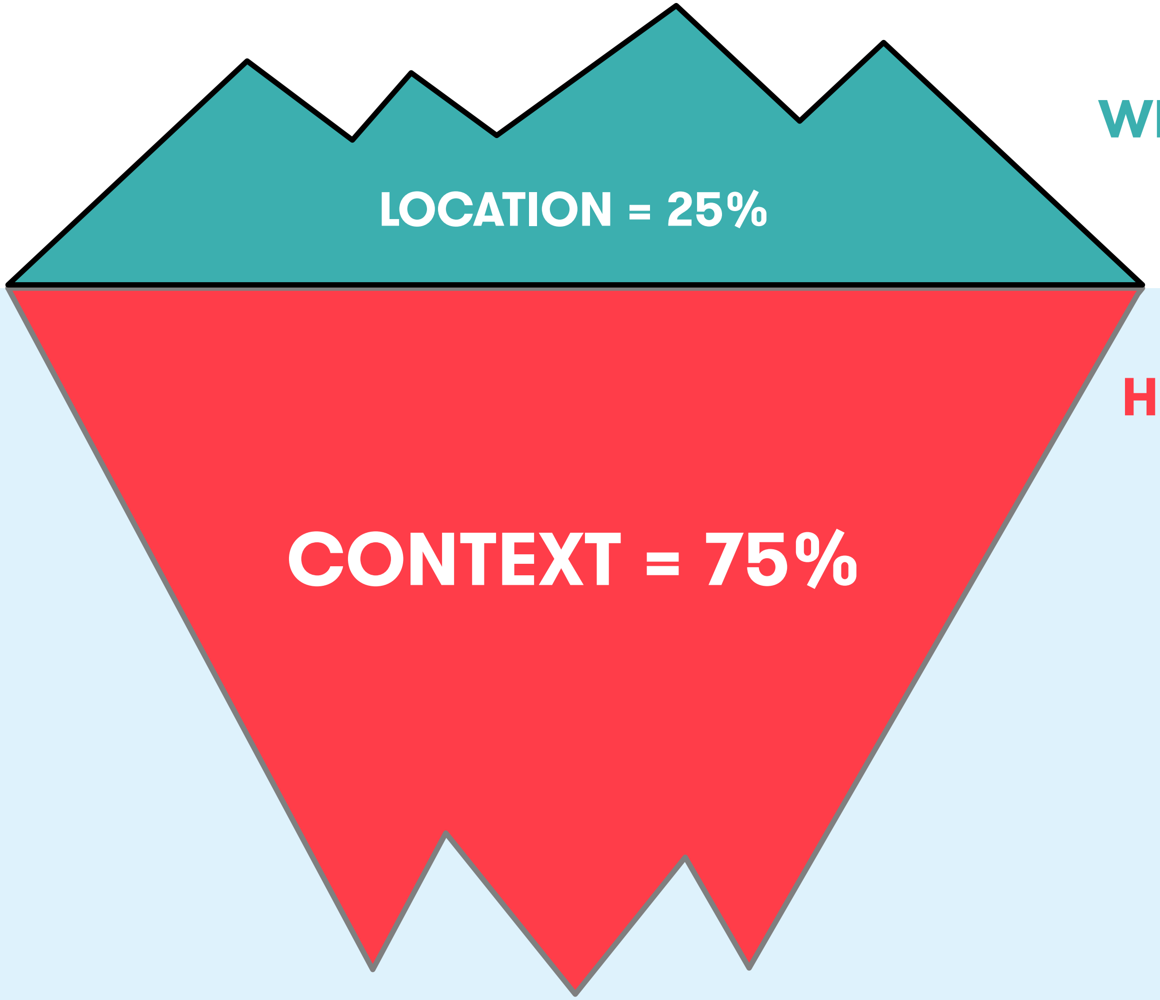
Result:

- Higher engagement (16%)

BUT

- Higher churn (+43% more app uninstalls)

Reason: Location based marketing is not enough



Where are your users going?

How are they getting there?

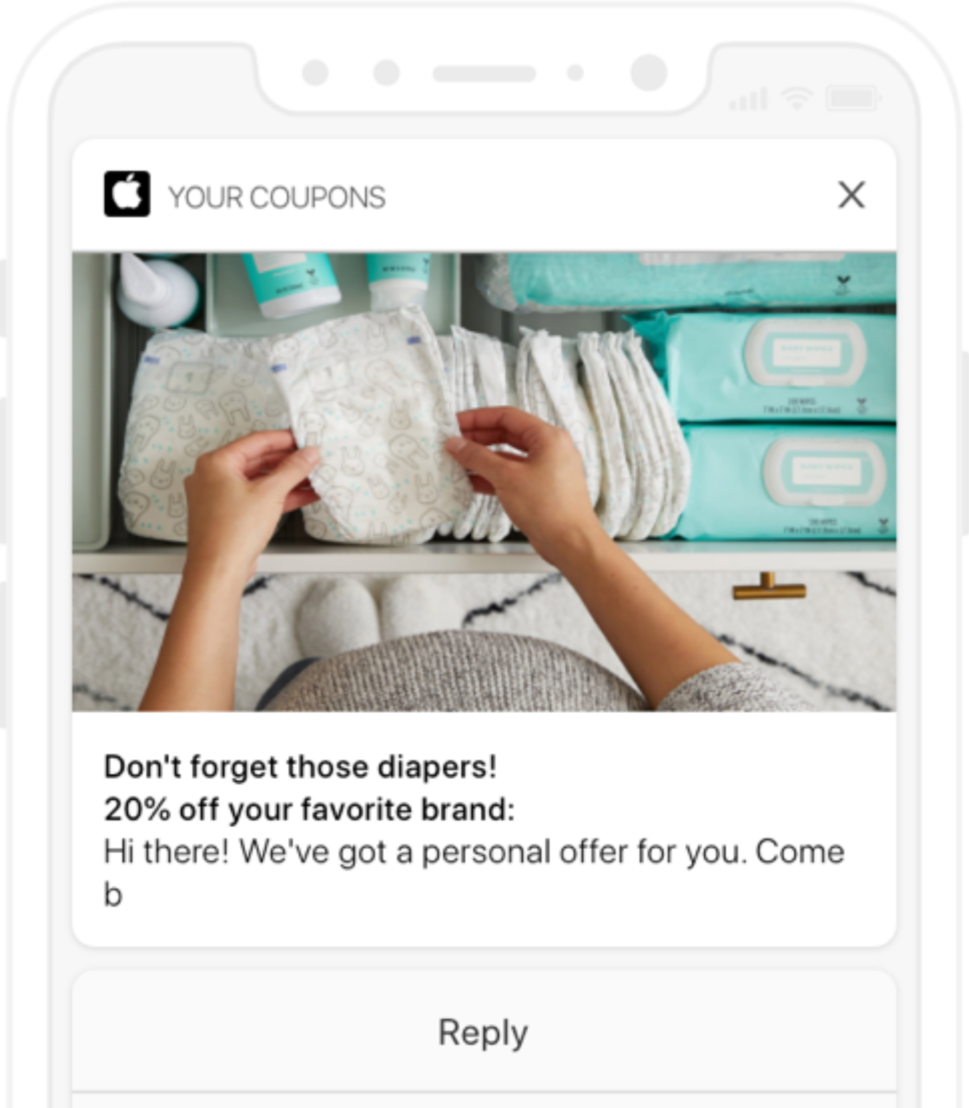
When are they going?

Why are they going?

How can AI solve this problem?

AI for behavioral modeling:

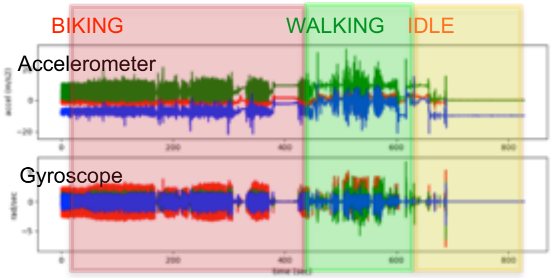
1. **What**
   User is currently **in transport**
2. **How**
   Transport mode is **car**
3. **Why**
   User is **dropping off kids** during morning commute
4. **Next**
   Predicted to **stop at the shop**
5. **Who**
   User is **brand-loyal** and has kids

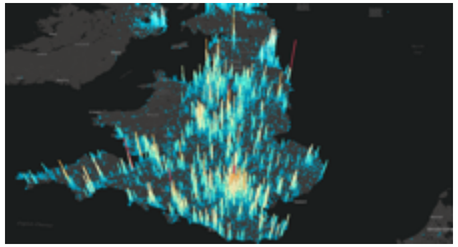


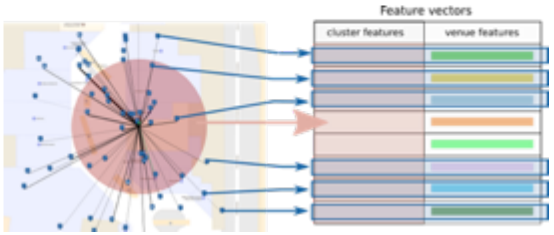
How can AI solve this problem?

Intelligence is needed:

1. **What & How**
   Activity detection
2. **Why**
   Intent modeling
3. **Next**
   Time-series prediction
4. **Who**
   Clustering and look-alike modeling

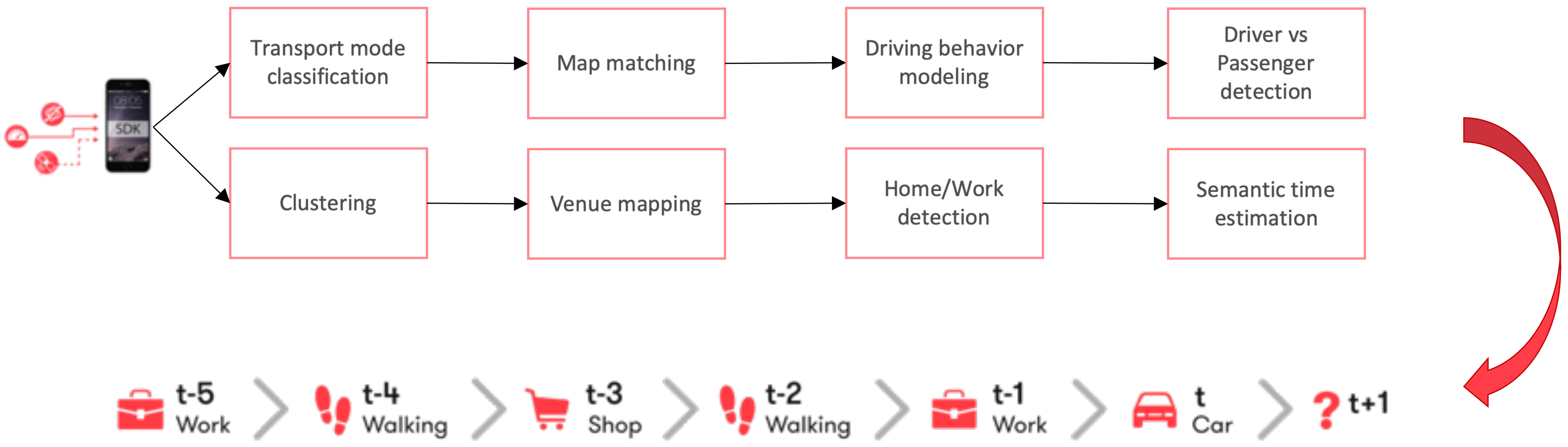




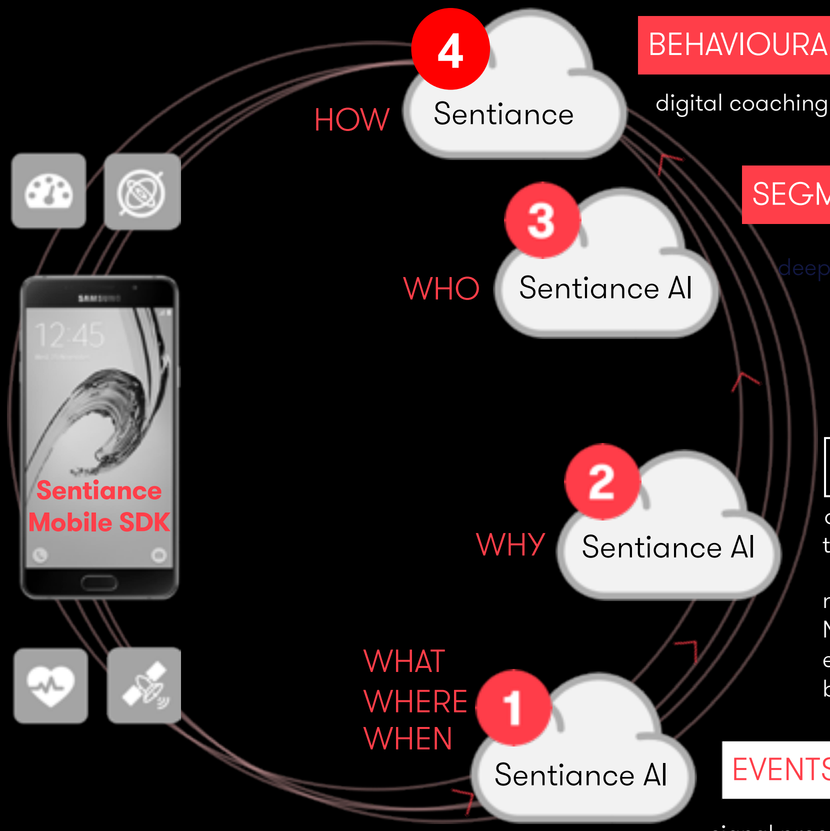


How can AI solve this problem?

Intelligence is needed:



How did we build it?



BEHAVIOURAL CHANGE | ENGAGEMENT

digital coaching – behaviour change – user engagement

SEGMENTS | PERSONALITY | HEADROOM | MOOD

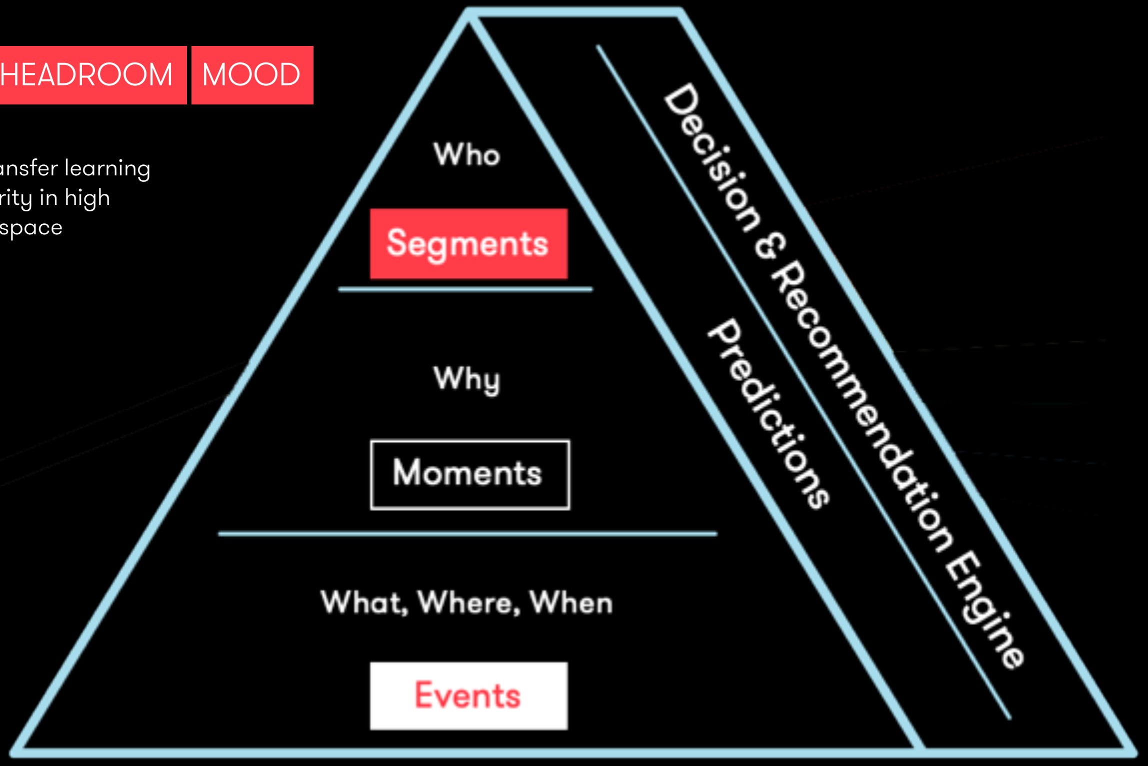
deep learning
semi-supervised by means of transfer learning
discover groups and user similarity in high dimensional behavioral feature space

MOMENTS

deep learning
time series => learn temporal patterns via deep recurrent neural networks
NLP techniques
extract meaning from behavioral timelines

EVENTS

signal processing + machine learning



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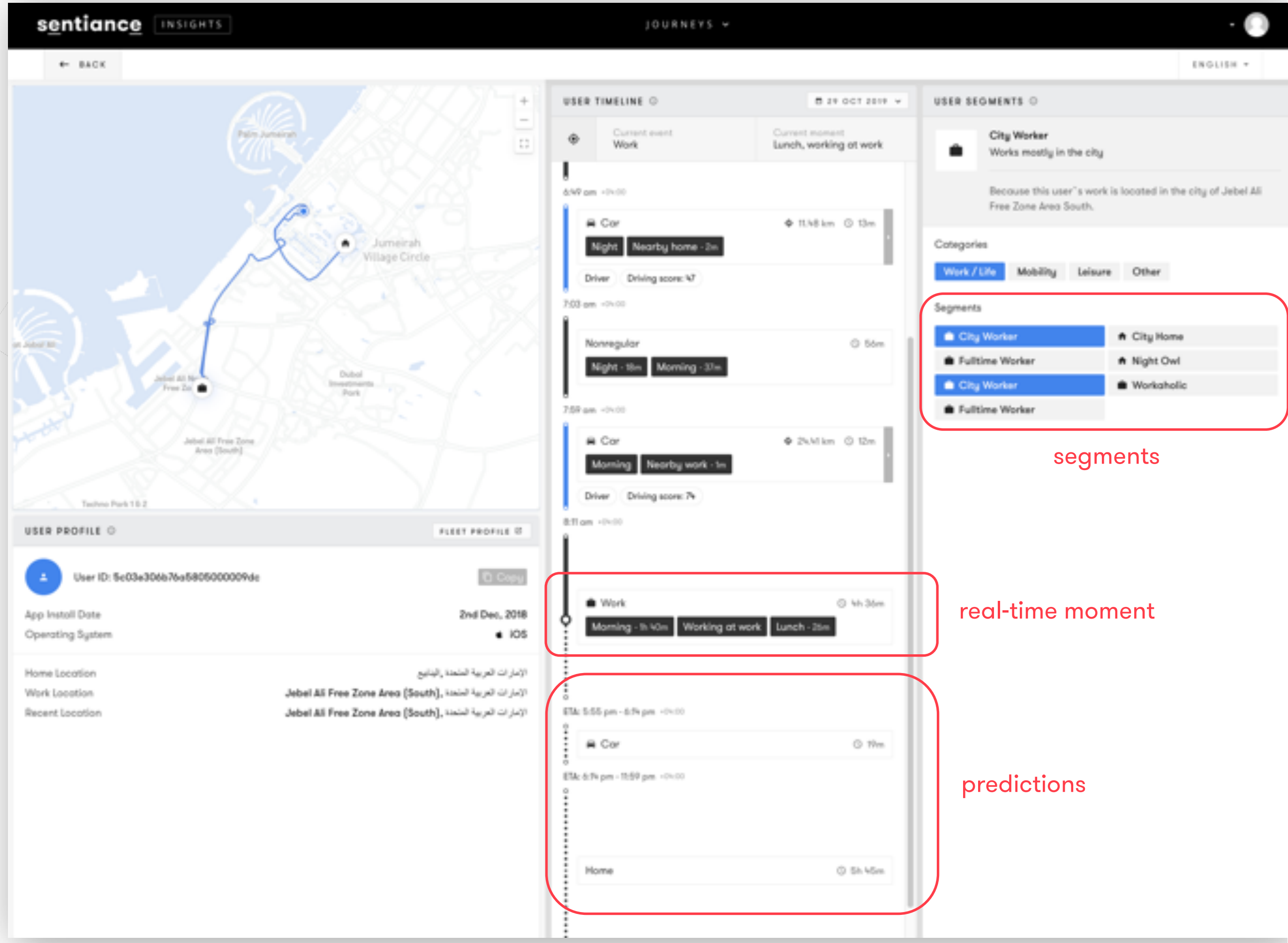
How did we build it?

A real example of hyper-personalization:

Research shows: *‘People are twice as likely to engage with mobile ads during commutes and in crowded areas”*

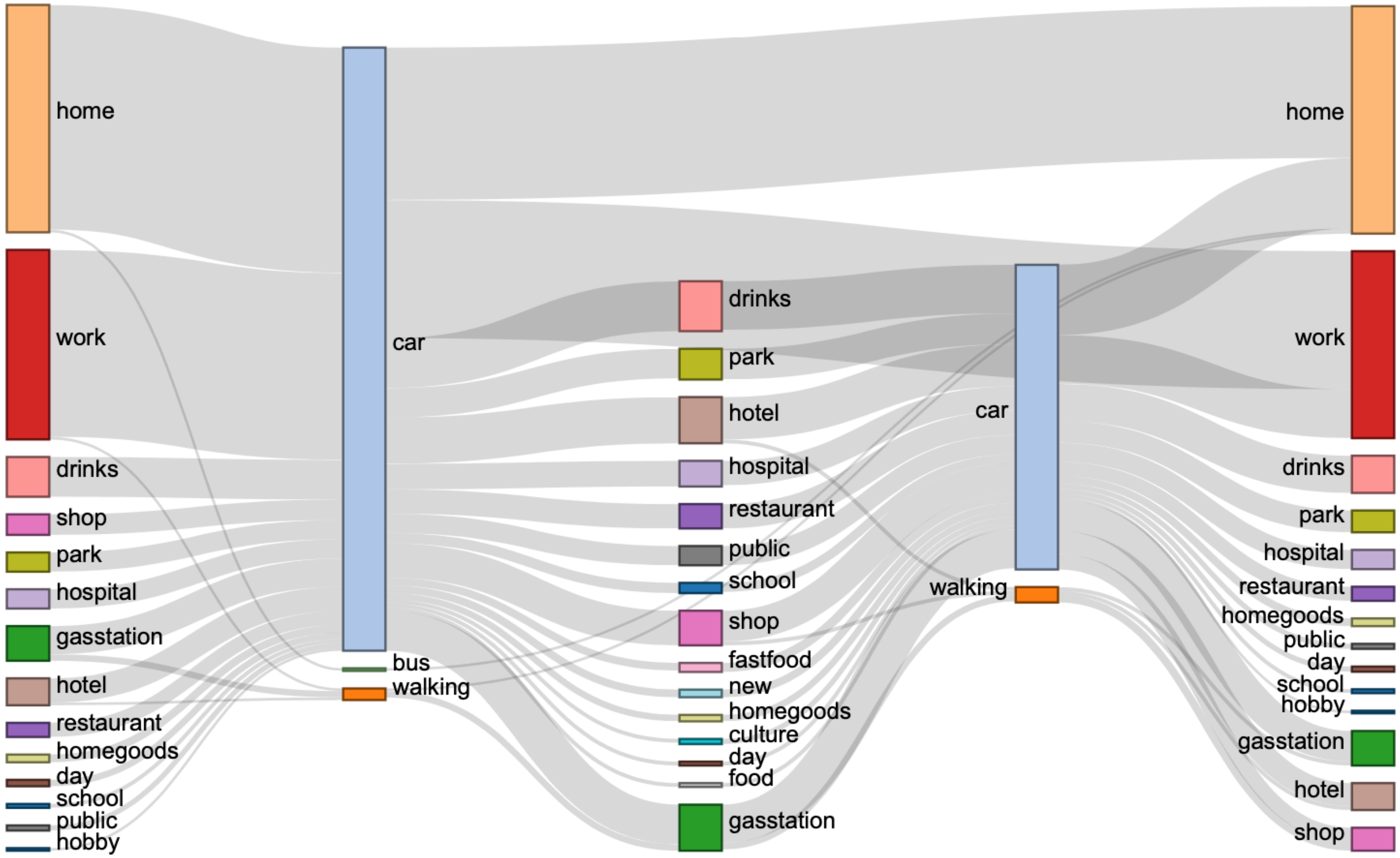
Our implementation:

- Send coupon to user if:
    - Event: ‘on a tram or train’
    - Moment: ‘In commute’
    - Prediction: ‘About to stop at a shop’
    - Segments: Brand-loyal, shopaholic, sportive
- **Results:**
    - Engagement increased 400%
    - Churn back to baseline levels



Some example insights for this customer

A day in life of a random user



Some segments assigned to this user:

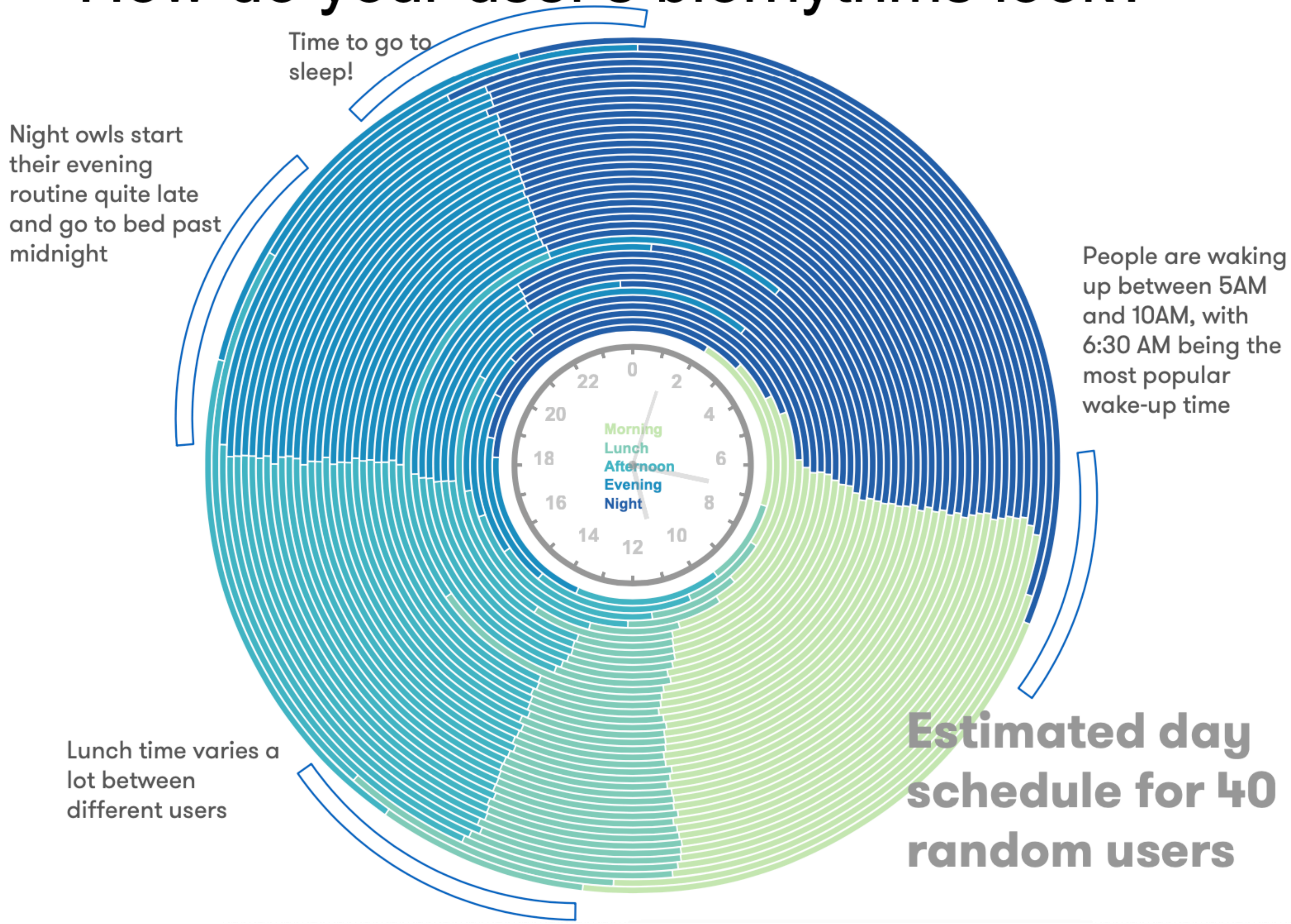
Nature lover

Work traveler

Brand loyal: Gas station

Detail can be added to the flow diagram by showing intermediate stops between origin and destinations. For example, it is clear that 'parking' is not a final destination for this user.

How do your user's biorhythms look?



340 Early birds

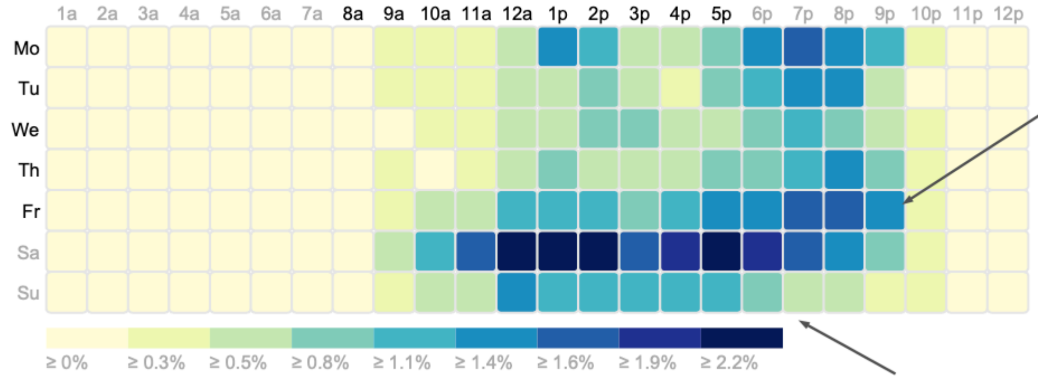
781 Night owls

205 Sleep deprived

Average semantic time:

When do your users shop?

Grocery shopping

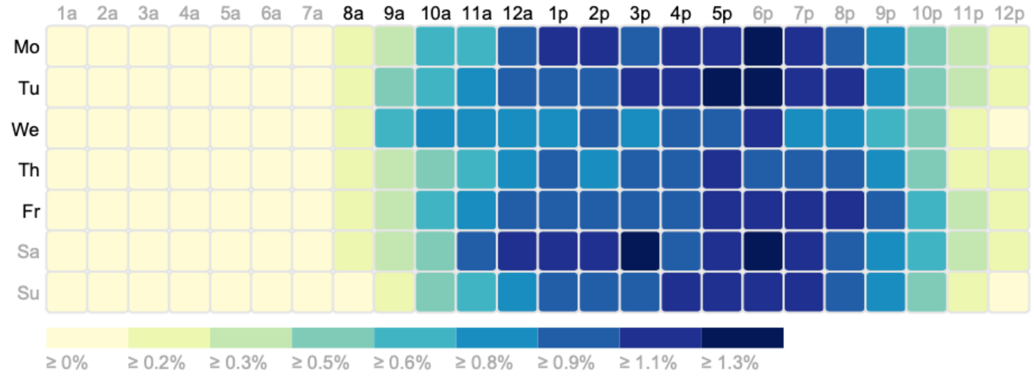


Friday late-evening shopping

Grocery shopping mostly happens on Saturdays before noon

Shops close early on Sundays

Other shopping



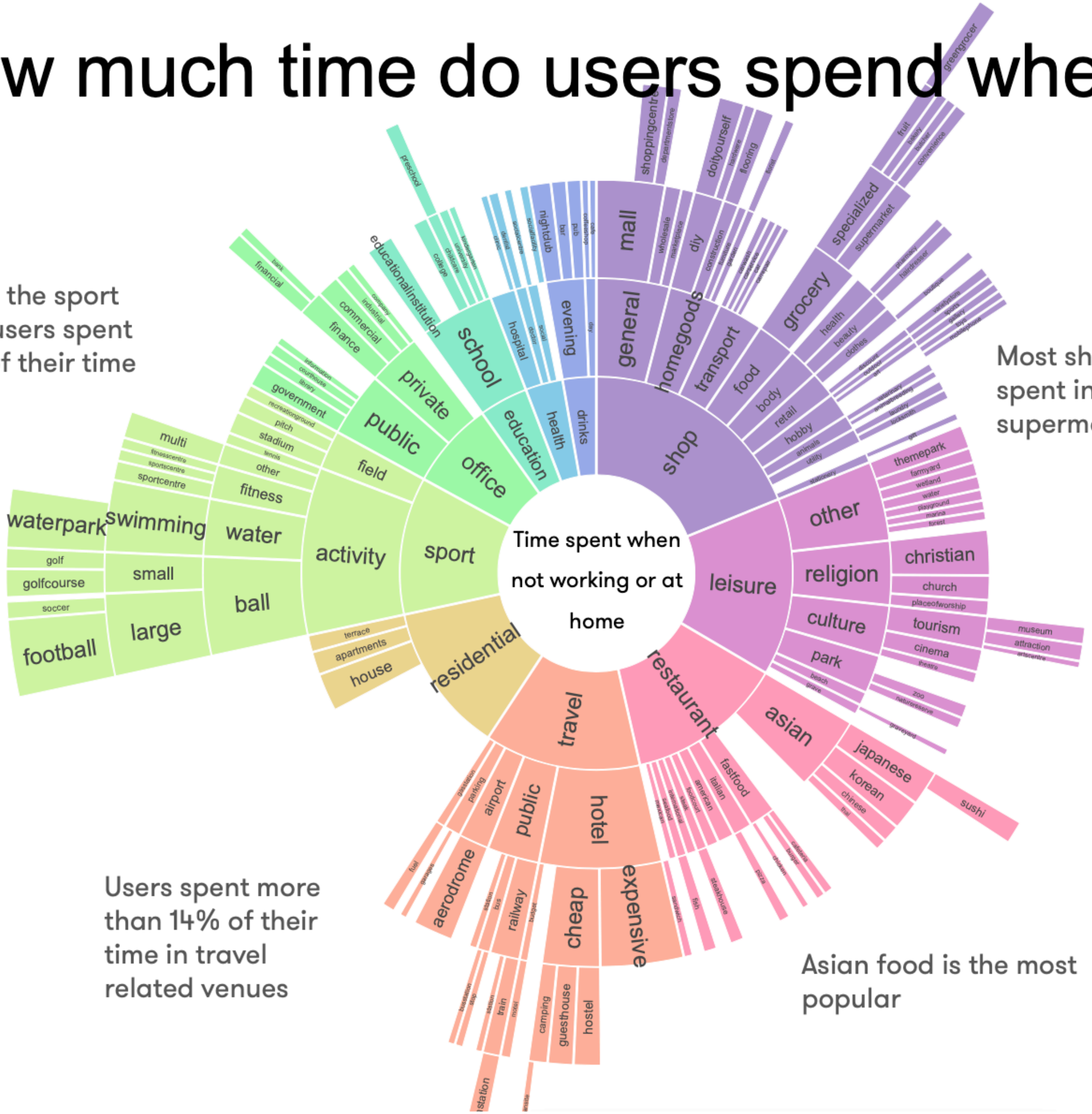
Non-grocery shopping (e.g. furniture and clothing) is more spread throughout the day

17% Grocery shopping

955 Brand-loyal users

77026 Shop visits

How much time do users spend where?



Football is the sport on which users spent the most of their time

Most shopping time is spent in malls and supermarkets

Users spent more than 14% of their time in travel related venues

Asian food is the most popular

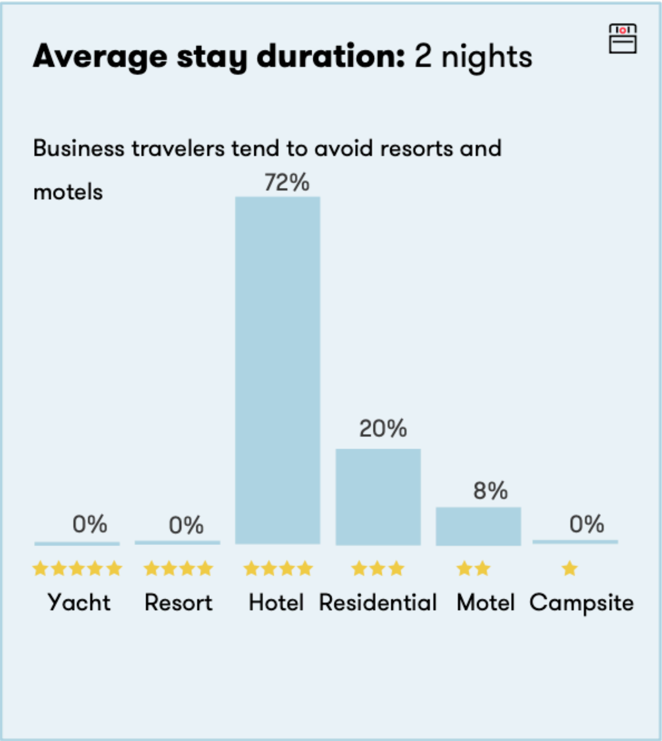
The least amount of time was spent in:

- **3%** Health
- **4%** Education
- **3%** Drinks

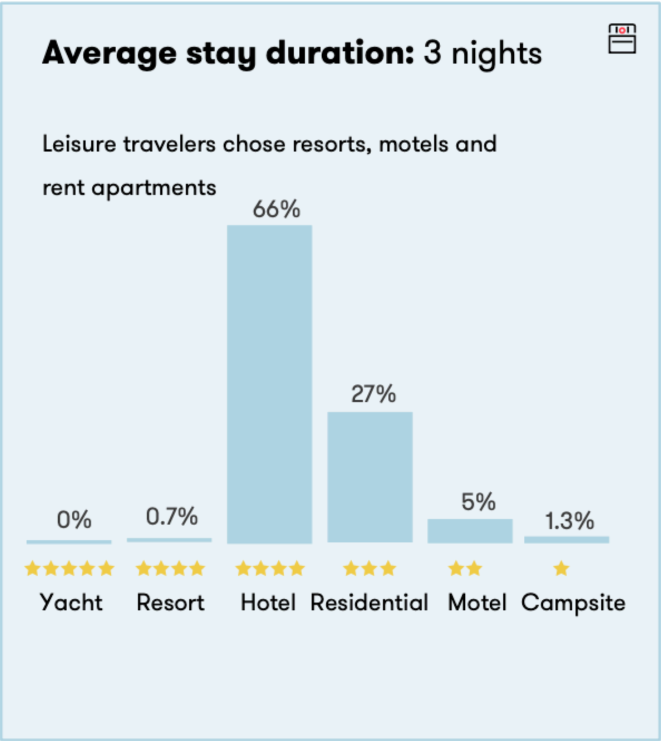
Durations are normalized per user, and averaged across the population. Working and commute related activities are excluded.

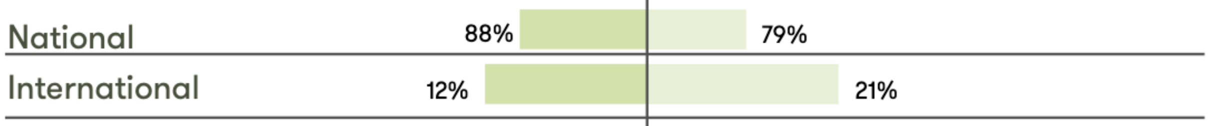
Leisure travelers go international

Business trips



Leisure trips





211 Beach visits

468 Cultural visits

524 Travelers

Longest stay:

Business: 17 nights

Leisure: 37 nights

Main lessons learned

Data is the new oil:

1. **Obtaining labeled data is expensive**
    - Pay students to walk around and label their transport mode
    - Use specialized companies to crowd-source data labeling: 50k EUR for 50 users x 30 days
    - Develop internal tooling for data cleaning and labeling

2. **Data is private**
    - Cannot be used to train models for other customers
    - First-party: Owned by the customer
    - Full transparency is the only way

Scalability matters:

1. **Mlflow: Manage the ML lifecycle**
    - Experimentation: Which parameters worked?
    - Reproducability: Which dataset was used?
    - Deployment: Versioning and continuous integration

2. **AWS helps us scale**
    - Elastic scaling: 15x higher load during peak hours!
    - Reproducibility: Which dataset was used?
    - One-off model training on expensive GPU machines

Do’s and Don’ts

Don’ts

1. **Let data scientists work on their own**
   - Developing a SOTA model in a notebook is easy
   - The hard part:
     - Deployment
     - Observability
     - Scalability
     - Reproducibility
   - For each Data scientist, you need 4 non-data scientists:
     - Data engineer
     - Machine learning engineer
     - Infrastructure engineer
     - Full-stack engineer
2. **Say that data science cannot be agile**
   - Doing research for months without baseline
   - Doing research for months without deployments
   - Research can be iterative!

Do’s:

1. **Data science as a citizen**
   - Easy access to data
   - Easy access to computational resources
   - Freedom to experiment
2. **Work product driven**
   - Data scientists like to aim for SOTA
   - Are super curious and like to build crazy stuff
   - We need some direction
   - Product team should drive AI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