UVA | SCHOOL *of* DATA SCIENCE

- Background
  - Project intros
  - Current state of the project
- Goal
  - Problem articulation
  - Has your idea been done by others?
- Dataset(s)
  - Basic EDA’s
  - Database set up
- Methods
  - What methods are you planning to use?
  - Any related literature to support your proposed methods?
- References

Capstone Project Proposal

Team Members: Griffin McCauley, Theo Thormann, Eric Tria, Jake Weinberg

Supervisor: Prof. Judy Fox

The Team

- **Griffin McCauley (Sc.B. Applied Mathematics & A.B. Economics)**
  - Model Design and Data Analysis
  - Liaison with the teaching staff
- **Theo Thormann (B.S. Environmental Science and Policy)**
  - Data Processing and Visualization
- **Eric Tria (B.S. Computer Science)**
  - Data Engineering and Analysis
- **Jake Weinberg (B.S. Commerce)**
  - Data Interpretation and Insights
  - Communications

Checklist of Goals

1. Understand trends in the data given to us by the client and figure out what data is useful in creating a model and what information is noise
2. Create a user retention model, which finds patterns in user events to identify user churn risk and predict resubscription behavior
3. Build an RNN to analyze the user event sequences on the platform
4. Produce a 6-page publishable paper (in IEEE format), along with an oral presentation, on our work summarizing what the model the team has created and what we have found using our model
5. Package and share our model, GitHub, and research findings with our client

Background

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- Customer data platform (CDP)
- Use that data to help publishers understand their customers and content
- Focus on educational publishers

Project Background

- Publishers want to maximize user retention
- To do this we will utilize user "events" to create models
- User events include pageviews, citations, scrolling activity, and more

	Fall
Goals	• Complete kickoff and onboarding • Gain subject matter expertise • Complete EDA ✓
Critical Activities	• Gain access to client data • Understand necessary analysis tools ✓

Goal: Create models using user events to maximize user retention and potentially other use cases for HUM

Tasks and Timeline

January

Finish all set up and background research to prepare for model execution

- Choose how to embed our data and input it to an RNN
- Determine what criteria to use for isolating training data and classifying users
- Coerce the data into the correct format and perform a trial run on a simple RNN model

February

Successfully complete initial training of user retention model

- Build code that comprises the backbone of our model

March

Refine the model and perform hyperparameter tuning

- Determine a subset of hyperparameters that we want to tune and select a reasonable range of values for these
- Retrain and evaluate the model for a variety of hyperparameter configurations

April

Prepare final model for deployment and ensure customizability for clients

- Extract insights from the model to market to clients
- Package the model for easy interpretability and implementation by our client

Weekly Workflow

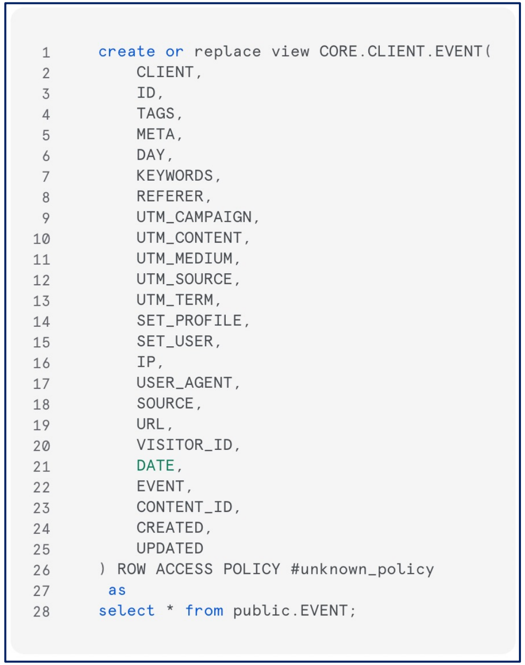
- Monday - Class session from 9:00-11:00am EST
  - Present weekly updates and next steps
  - Discuss current state of project with teaching staff
- Tuesday - Collaborative group session from ~11:00am-12:30pm EST
  - Continue to progress on weekly tasks while also discussing implementation techniques, new findings, and potential roadblocks
- Thursday - Sponsor meeting from 12:00-1:00pm EST
  - Present the results of the past week’s tasks
  - Discuss the current trajectory of development and ask any pertinent questions related to the design or methodology incorporated in the model
  - Plot out goals for the coming week
- Work towards completing individual assignments during the remaining days

Datasets

- Use first-party customer data, which includes user events/actions collected by the client
  - Example events are page views, page scrolls, and citations
- The data is mostly cleaned for us by our client, our group will engineer the data to effectively prepare it for use in the model
- Data is hosted on Snowflake
  - We will use Python integration through the Snowpark API
- Machine Learning models will run on AWS SageMaker

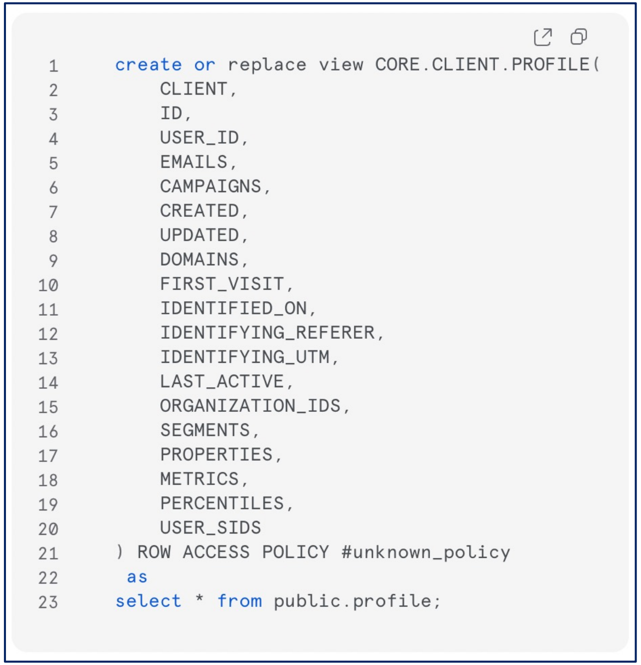
Datasets

EVENT



```sql
create or replace view CORE.CLIENT.EVENT(
    CLIENT,
    ID,
    TAGS,
    META,
    DAY,
    KEYWORDS,
    REFERER,
    UTM_CAMPAIGN,
    UTM_CONTENT,
    UTM_MEDIUM,
    UTM_SOURCE,
    UTM_TERM,
    SET_PROFILE,
    SET_USER,
    IP,
    USER_AGENT,
    SOURCE,
    URL,
    VISITOR_ID,
    DATE,
    EVENT,
    CONTENT_ID,
    CREATED,
    UPDATED
) ROW ACCESS POLICY #unknown_policy
 as
select * from public.EVENT;
```

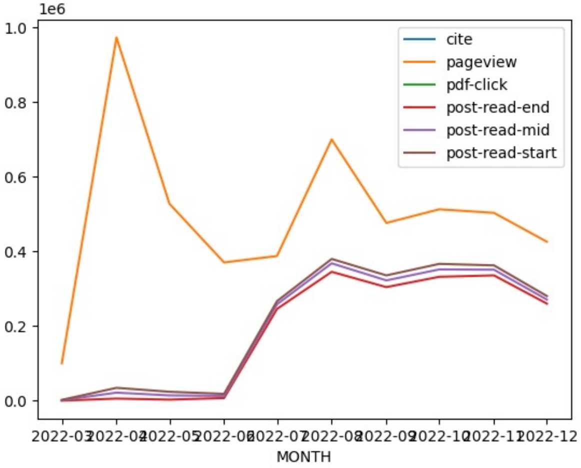
PROFILE

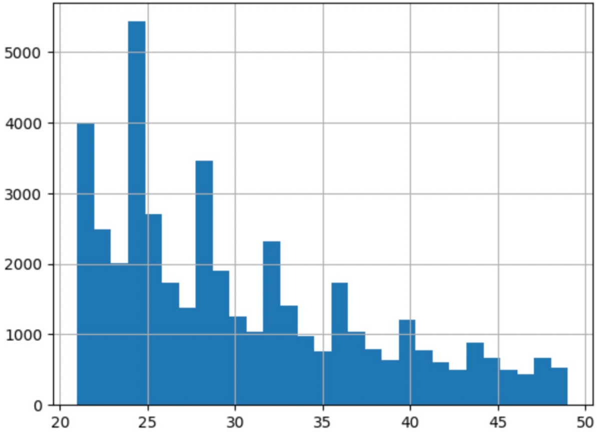


```sql
create or replace view CORE.CLIENT.PROFILE(
    CLIENT,
    ID,
    USER_ID,
    EMAILS,
    CAMPAIGNS,
    CREATED,
    UPDATED,
    DOMAINS,
    FIRST_VISIT,
    IDENTIFIED_ON,
    IDENTIFYING_REFERER,
    IDENTIFYING_UTM,
    LAST_ACTIVE,
    ORGANIZATION_IDS,
    SEGMENTS,
    PROPERTIES,
    METRICS,
    PERCENTILES,
    USER_SIDS
) ROW ACCESS POLICY #unknown_policy
 as
select * from public.profile;
```

Datasets (EDA)

- Recurring events to use: citation, pageview, pdf-click, post-read-start, post-read-mid, post-read-end
- Subset of users with 20-50 events in 2022 represents a significant portion of overall data





Methods

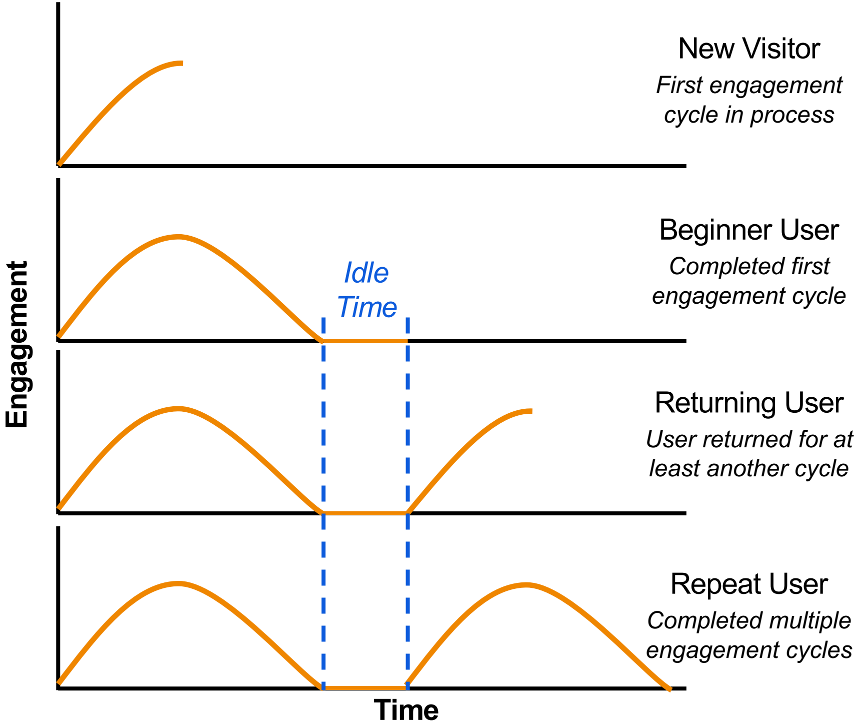
- We currently plan on implementing an RNN for the user retention model
  - Our sequence data will contain information regarding the event type and time of execution, and we will likely use an event-time joint embedding (Li et al., 2017) in order to incorporate both components into the model input

- Details of the model architecture are still under consideration
  - Potential use of an LSTM hidden layer for capturing longer-term sequence dependencies
  - Probable use of a softmax activation layer for multiclass classification of the output

- Depending on client needs, we may also add another RNN for sequence classification in addition to next-step event prediction

Retention Model Path Forward

User Archetype Approximations


New Visitor
First engagement cycle in process
Beginner User
Completed first engagement cycle
Idle Time
Returning User
User returned for at least another cycle
Repeat User
Completed multiple engagement cycles
Engagement
Time

Proposed Modeling Technique

- Leverage idle time interval as special event to denote period of disengagement
  - Mark as idle if greater than 95% of users' event gaps
  - Preliminary value of ~73 hours of idle time between event cycles per user (~280 hours as initial benchmark for churned out based on 90% quantile of users' maximum event gaps)
- If an event sequence is not idle, predict the rest of the events until idle period is expected
  - Then, use most recent completed sequence to predict whether the user will return
- Sequence length of interest appears to be 16-48 events
- Next steps would be to encode sequences of the desired lengths and to perform training for both sequence prediction and classification

Conclusions & Future Work (TBD)

- What solutions you have accomplished and how do they compare with related work?
- Any insights or observations from this work?
- What can be done in future work?

References

- Li, Y., Du, N., Bengio, S. (2017, July 31). Time-Dependent Representation for Neural Event Sequence Prediction. Arxiv. Retrieved January 12, 2023, from https://arxiv.org/abs/1708.00065
- Savsunenko, O. (2020, January 4). How-to encode time property in recurrent neural networks. Towards Data Science. Retrieved January 12, 2023, from https://towardsdatascience.com/how-to-encode-time-property-in-recurrent-neutral-networks-friday-experiment-c14c39ba9755