Personalized Engagement
The Art of Reconnecting with Email Subscribers

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Problem Statement

Context: McKinsey Global Publishing runs an email program featuring +40 newsletters and topic-based notifications. Subscriber engagement amplifies McKinsey's thought leadership among target audiences, including clients and potential clients. Ongoing email communications with subscribers is critical in nurturing and extending those relationships.

Newsletter — Subscribers engage with content — Expansion of McKinsey's thought leadership
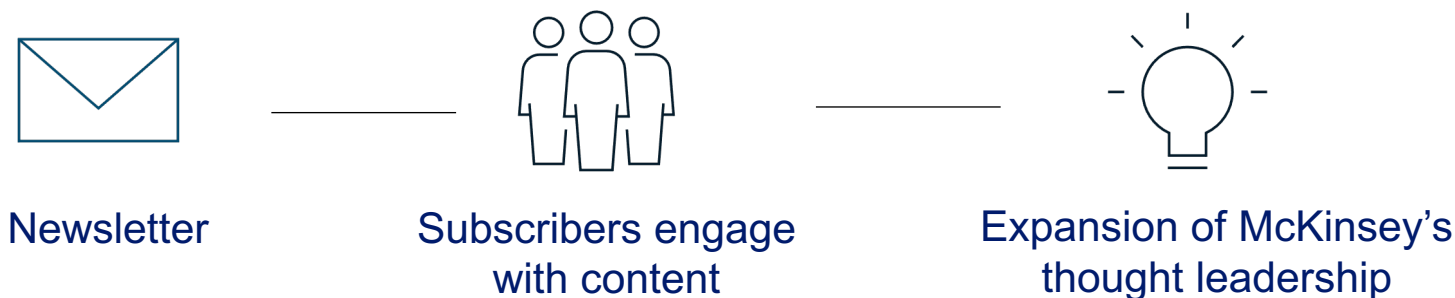
Some percentage of email subscribers become inactive within a year. **A one-size-fits-all retention strategy was doing little to reengage many of those readers.**

One-size-fits-all re-engagement email

Personalized re-engagement email
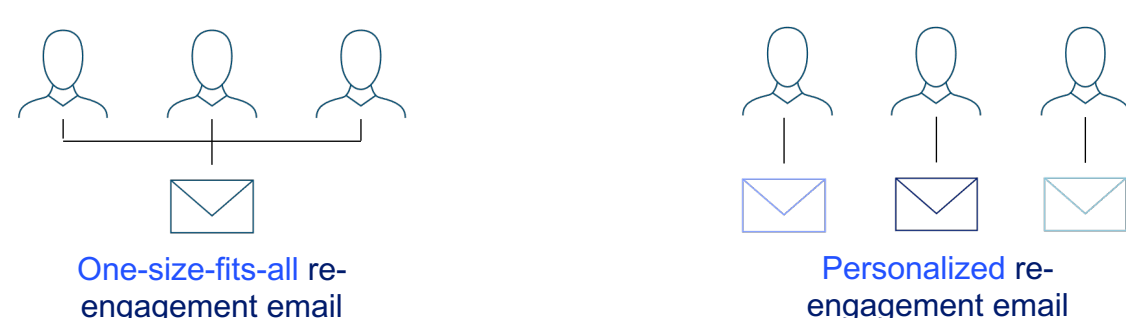
Objective

The central objective of this project is to
- Target the right subscribers
- At the right time
- With the right content

To increase user engagement and reduce churn.

Datasets

User data
Demographic & subscription details

Activity data
User engagement data e.g. click/open rate on newsletter and website

Content data
*Content type, authorship, URL, topic, industry*

Methodology

Target the right subscribers
Time Series User Clustering

Goal: Identify groups of subscribers with similar engagement patterns over time

1. Align users to a common starting point to visualize the number of months since user joined
2. Filter subscribers that have not reached a 12-month tenure
3. Leverage Time Series clustering with user engagement patterns to identify groups of similar users
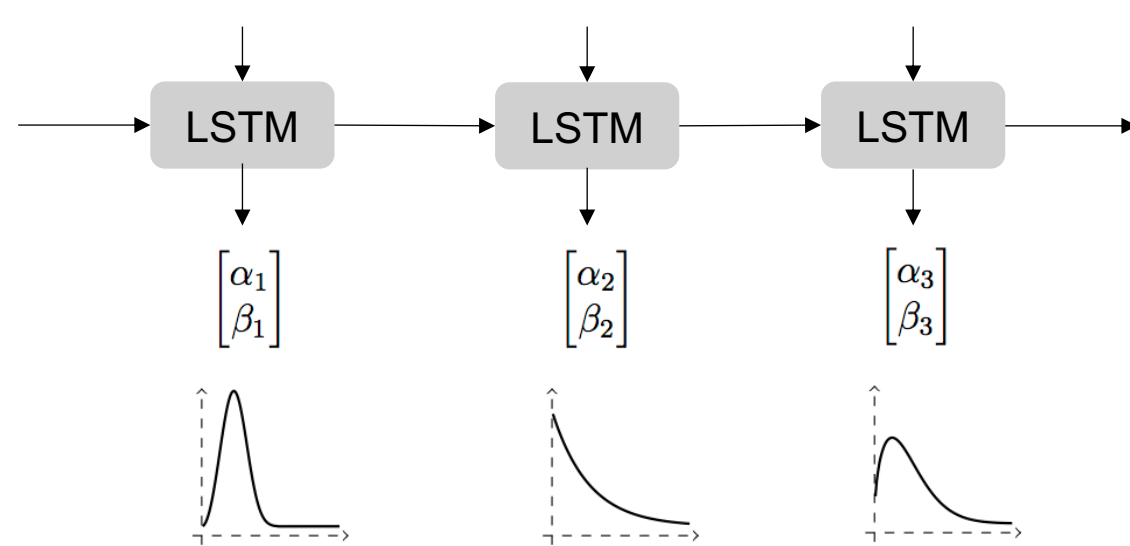
Open Rate vs Months since sign-up
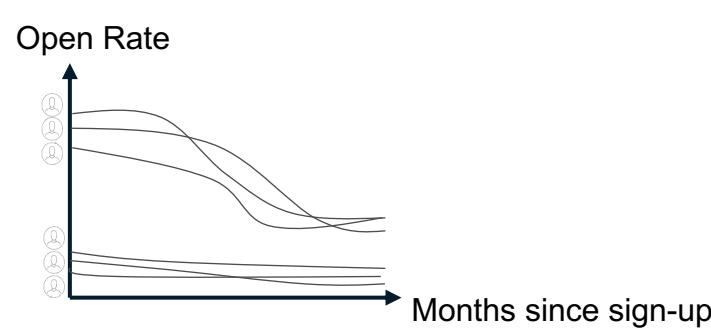
At the right time
Churn Prediction

Goal: Predict when user groups are at risk of churn

Weibull Time-To-Failure Long-Short-Term-Memory (LSTM) network combines survival analysis and deep learning to predict time-until-churn per user. **Additional interpretability was achieved by analyzing the coefficients of traditional survival analysis regression methods**
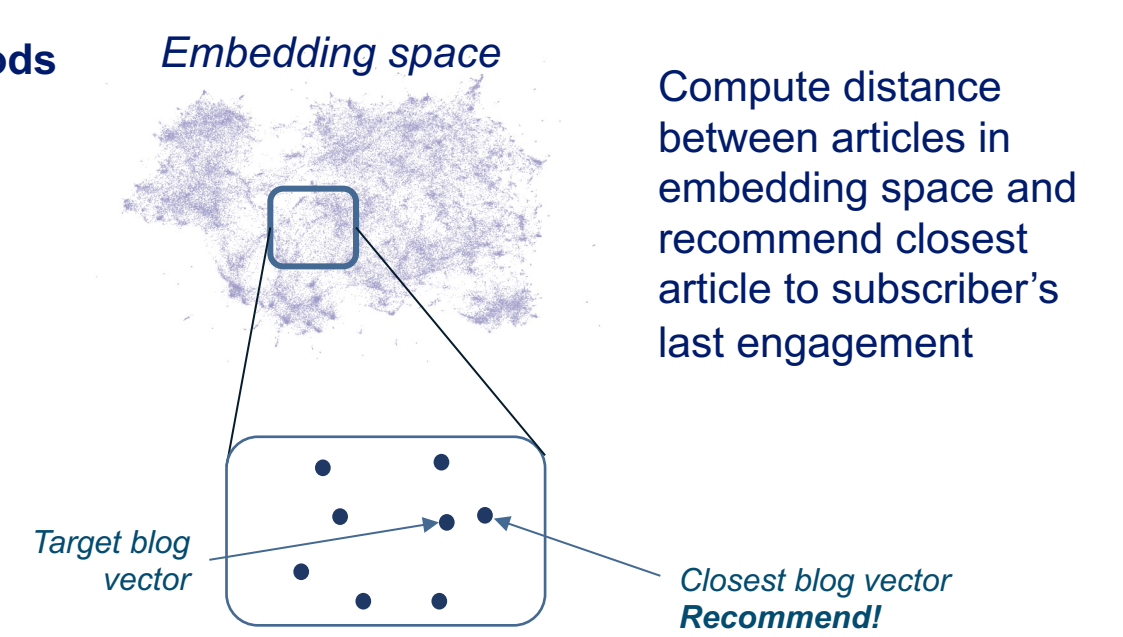
LSTM → LSTM → LSTM

$\begin{bmatrix}\alpha_1 \\ \beta_1\end{bmatrix}$ $\begin{bmatrix}\alpha_2 \\ \beta_2\end{bmatrix}$ $\begin{bmatrix}\alpha_3 \\ \beta_3\end{bmatrix}$

Predict a Weibull probability distribution (defined by parameters alpha and beta) each month, centered around the number of months until churn

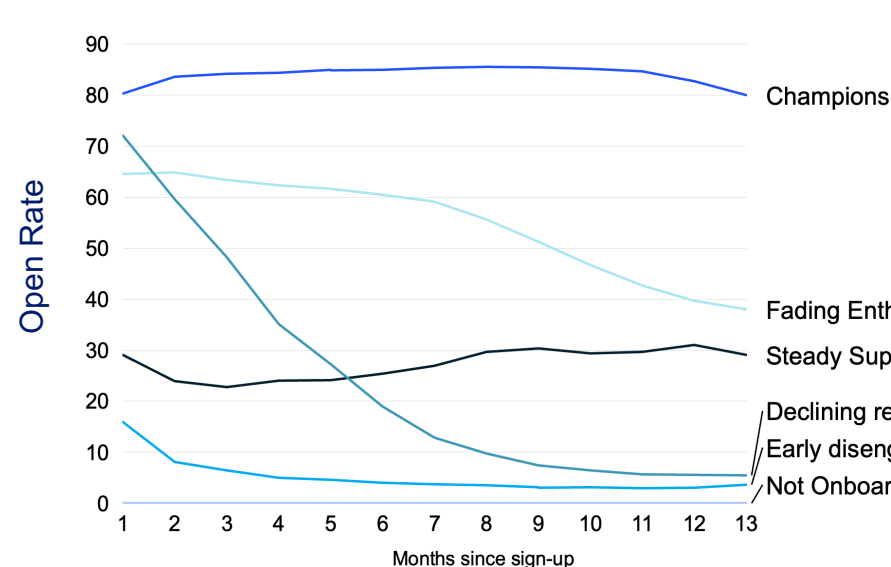### With the right content
Content Recommendation

Goal: Re-engage users at risk with similar content to previously opened/clicked
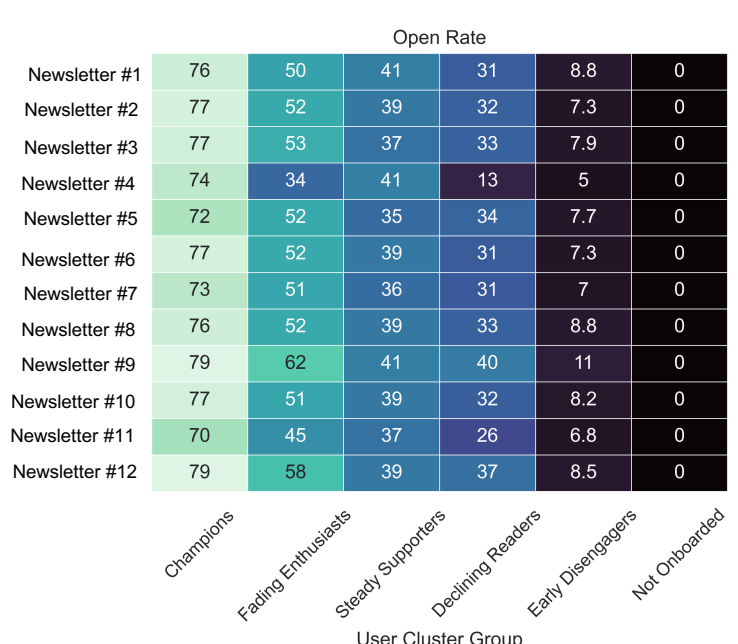
Embedding space

Compute distance between articles in embedding space and recommend closest article to subscriber's last engagement

Target blog vector   *Closest blog vector* **Recommend!**

Results

User Clustering

We identified 6 clusters of engaged users

Open Rate vs Months since sign-up — Champions, Fading Enthusiasts, Steady Supporters, Declining readers, Early disengagers, Not Onboarded

Clusters of user engagement 12 months since sign-up. Open Rate (open/delivered) in percentage

Open Rate	Champions	Fading Enthusiasts	Steady Supporters	Declining Readers	Early Disengagers	Not Onboarded
Newsletter #1	76	50	41	31	8.8	0
Newsletter #2	77	52	39	32	7.3	0
Newsletter #3	77	53	37	33	7.9	0
Newsletter #4	74	34	41	13	5	0
Newsletter #5	72	52	35	34	7.7	0
Newsletter #6	77	52	39	31	7.3	0
Newsletter #7	73	51	36	31	7	0
Newsletter #8	76	52	39	33	8.8	0
Newsletter #9	79	62	41	40	11	0
Newsletter #10	77	51	39	32	8.2	0
Newsletter #11	70	45	37	26	6.8	0
Newsletter #12	79	58	39	37	8.5	0

User Cluster Group
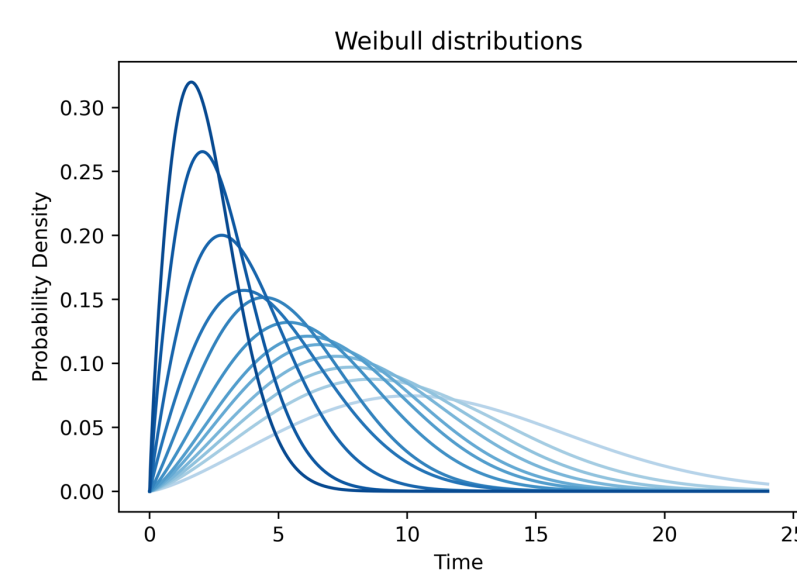
Open rate heatmap per newsletter

Churn Prediction

We predicted months until churn for each user at each time step

Time to Churn vs Time — Truth, Predicted, 90% CI around mode
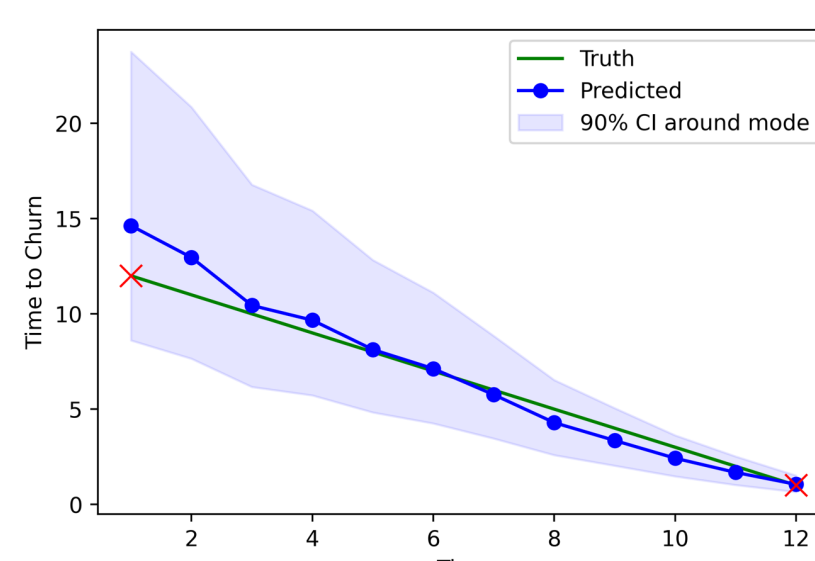
1.8
months Mean Absolute Error (MAE) out-of-sample with only 6 months of data

As we gather more data on each user, predictions get more accurate (from 2.5 MAE with 3 months of data, to 1 MAE with 9 months of data) and with a narrower confidence interval.

Weibull distributions — Probability Density vs Time

Predictions for one user at different time steps. This user churned after 12 months from sign-up.

A/B Testing

Ran an A/B testing re-engagement campaign to test recommended strategies

~10%
Of subscribers headed-towards-churn got re-engaged

Cohorts of subscribers tested were those who registered January 2023 to May 2023 and were considered headed-towards-churn given our predictions.
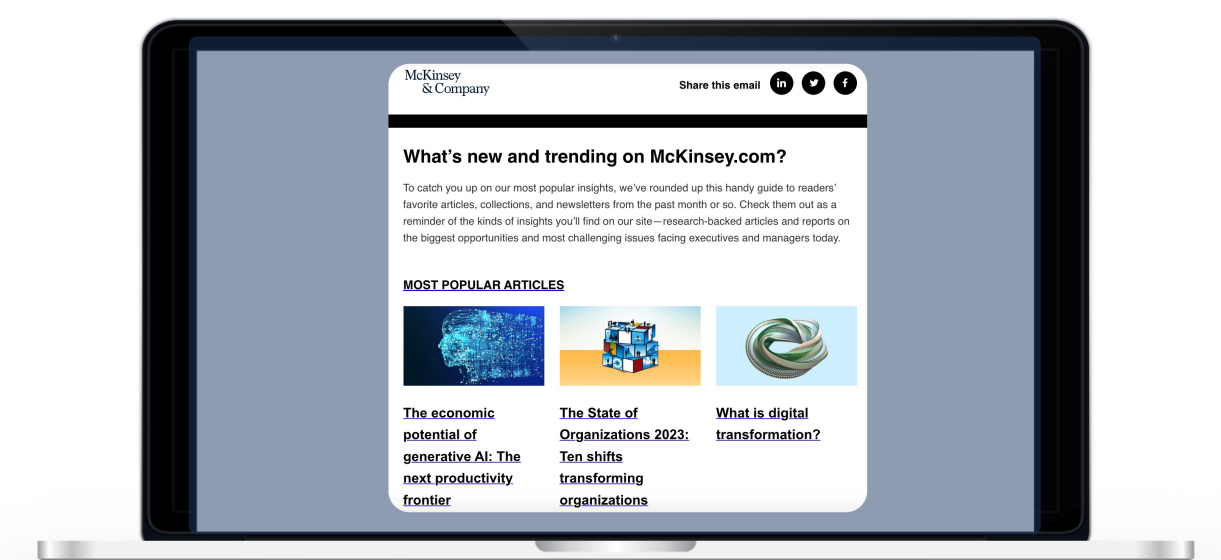
Re-engagement email sample.

Business Impact

- Expected to reduce number of **subscribers headed-towards-churn by ~10%**
- **Delivery of actionable recommendations on when to target** subscribers with 1.8 months Mean Absolute Error
- **Implemented in production** to target at-risk users every month

Future Work

- ☑ Automate delivery of re-engegement emails
- ☑ Expand methodology to other areas of Publishing - e.g., leveraging content recommendations on the site, identifying disengaged users on the site or app.
- ☑ A/B test further re-engagement campaigns at various months before churn

"One of the most actionable hypothesis + recommendations reports I have seen in my three plus decades in publishing, in an area that is vital to the future of McKinsey's continued ability to reach and engage global audiences in our ongoing 'insights to impact' digital storytelling journey."

- Raju Narisetti
Leader and Publisher, Global Publishing

"In my role, leading product development and analytics for McKinsey.com, this work is a standout in its actionable recommendations for our subscriber base. It will enable us to boost engagement, reduce churn, and contribute to converting readers into clients. We are thrilled about the opportunities this analysis will bring."

- Marianne Blum
Director External Engagement, Tech Ecosystem