<u>ML System Design for Personalized Newsfeed</u>

<u>Objective</u>: Build a system that surfaces relevant, engaging, and personalized content for each user. Maximize user engagement (as a set of interactions)

<u>Clarifying Questions:</u>

1. What specific user actions (e.g., likes, clicks, shares, dwell time) are we aiming to increase?
2. Do we show only posts or also activities from other users?
3. What types of data do the posts include? (text, image, video)?
4. Content Freshness: How important is it to prioritize real-time content (e.g., breaking news)?
5. Real-Time Constraints: How frequently should recommendations update to reflect recent user behavior?
6. Do we have negative feedback features (such as hide ad, block, etc)? Assumption – this is not there.
    1. How do we collect negative samples? (not clicked, negative feedback).
7. What type of user-ad interaction data do we have access to can we use it for training our models?
8. How fast the system needs to be?
9. What is the scale of the system?
10. Is personalization needed? Yes

Requirements; Latency: 200 msec of newsfeed refreshed results after user opens/refreshes the app
Scalability: 5 B total users, 2 B DAU, refresh app twice

<u>Define the ML Task:</u>

- Recommendation Task: This is primarily a recommendation problem where the goal is to predict which content each user is most likely to engage with.
- Classification/Ranking Task: Frame it as a ranking problem where content is scored and ordered based on its relevance to the user.
- Objective: maximize number of explicit, implicit, or both type of reactions (weighted)
    - implicit: more data, explicit: stronger signal, but less data -> weighted score of different interactions: share > comment > like > click etc
    - I/O: I: user_id, O: ranked list of unseen posts sorted by engagement score (wighted sum)
    - Category: Ranking problem: can be solved as pointwise LTR with multi/label (multi-task) classification

<u>Data</u>

Inputs:

1. User Data

- User Profile Information:
  - Demographics: Age, gender, location, language.
  - Interests: Explicitly stated interests or inferred topics of interest.
  - Account Details: Date joined, subscription level (if applicable), device types used.
- User Behavior and Interaction History:
  - Engagement Metrics: Clicks, likes, shares, comments, reactions.
  - Browsing and Reading Patterns:
    - Dwell Time: How long they spend on an article.
    - Scroll Depth: How much of the content they scroll through.
    - Session Duration: Length of time per session.
  - Interaction Recency: How recently the user interacted with the app, and their interaction frequency.
  - Historical Data: Articles read, topics, categories, authors previously engaged with.
  - Time of Engagement: Times of day or days of the week they're most active.
- User Preferences:
  - Content Type Preferences: Preferences for certain types of media (articles, videos, images).
  - Source Preferences: Preferred publishers, authors, or content sources.
  - Topics of Interest: Inferred from historical engagement data, explicit topic selections.
  - Sentiment/Emotion Analysis: Potentially inferred from reactions or comments, e.g., preference for positive or negative news.

2. Content Data

- Content Metadata:
  - Category and Topic: High-level categories (e.g., sports, politics) and specific tags or keywords.
  - Content Type: Format of the content, such as article, video, slideshow, or infographic.

- Length and Complexity: Word count, reading level, and media richness (multimedia vs. text-heavy).
- Author Information: Author profile, popularity, and prior engagement with the user.
- Source/Publisher Information: Publisher reputation, brand preferences, etc.
- Popularity Metrics: General popularity, such as overall likes, shares, or trending status.
- Publish Date and Time: How recently the content was published, used to gauge freshness.

- Content Embeddings:
  - Precomputed embeddings of articles or videos based on NLP techniques or topic modeling. These can capture semantic relationships among content and help in aligning with user preferences.

3. Contextual Data

- Temporal Context:
  - Time of Day: Users may prefer different types of content at different times (e.g., quick reads in the morning, in-depth in the evening).
  - Day of the Week: Users may engage with different topics on weekdays vs. weekends.
  - Seasonality or Events: Specific trends or topics may peak around events (e.g., holiday seasons, elections, sports events).
- Device and Platform Context:
  - Device Type: Desktop, mobile, tablet—content layout and type may vary based on device.
  - Operating System and Browser: To optimize user experience, especially if specific types of content render better on certain platforms.
  - App vs. Web: Interaction patterns may vary depending on whether the user is using the app or the web version.
- Location-Based Context:
  - Geolocation: City, state, or country-level location, which can influence regional preferences.
  - Weather Information: Weather conditions may impact content preferences (e.g., planning activities).
- User Session Context:
  - Session Duration and Engagement: Whether it's the user’s first session of the day, total engagement length, and activity level during the session.

- Current Activity: Engagement with specific topics or sections within the app during the session.

Outputs:

- A ranked list of content items that are personalized for each user's feed.

Feature Engineering

1. User Features

- Demographic Features:
    - Age Bucketing: Group ages into ranges (e.g., 18-24, 25-34) to generalize and reduce dimensionality.
    - Location Encoding: Use one-hot encoding or regional embeddings for user location (city, state, or country).
    - Language Preferences: One-hot encode or use embeddings to capture preferred languages.
- Behavioral and Interaction Features:
    - Click-Through Rate (CTR): Calculate CTR per topic, content type, or category. These features show which types of content the user tends to click on.
    - Engagement Score: Combine clicks, likes, shares, comments, and average reading time into a single engagement metric, weighted to emphasize certain actions.
    - Recent Interactions: Create features representing recent interactions, such as the topics of the last few articles the user clicked on, read, or engaged with.
    - Time of Day and Day of Week Preferences: Aggregate engagement data by hour and day, capturing when the user is most active, which can be useful for real-time recommendations.
    - Content Consumption Diversity: Measure the diversity of topics the user engages with (e.g., entropy of topic distribution). Users with high diversity may need more varied recommendations.
- Historical Interest Trends:
    - Topic Affinity: Track long-term interests by calculating average engagement metrics per topic (e.g., "sports," "technology") over a long history.
    - Temporal Interest Decay: Apply a time decay factor to engagement scores, giving more weight to recent activity than older activity. Exponential decay functions work well here.
- Session-Based Features:

- Session Length and Frequency: Track the average number of articles consumed per session and the frequency of sessions per day or week.
- Scroll Depth and Completion Rate: Features to capture whether users read articles fully, partially, or just skim.

2. Content Features

- Text-Based Features:
  - Content Embeddings: Use NLP models (e.g., BERT or word2vec) to create embeddings of article text, capturing the semantic meaning. This can be used to match content to similar articles.
  - Topic Modeling: Use techniques like LDA or clustering to assign topics or tags to articles, converting content into a more structured form.
  - Sentiment Analysis: Analyze the article text to derive sentiment scores. These scores can help match content to users who prefer positive or negative tones.
- Metadata Features:
  - Category and Subcategory: One-hot encode or use embeddings to represent the high-level category of the article (e.g., sports, tech, health).
  - Length of Content: Use article length as a feature. For example, short vs. long content can be important for matching user session length preferences.
  - Author Popularity: Track and add engagement metrics (e.g., average article views) for each author, so popular authors can be boosted in recommendations.
- Popularity and Trending Scores:
  - Global Popularity: Overall engagement metrics (e.g., clicks, shares) for each piece of content, indicating general popularity.
  - Relative Popularity: Calculate popularity within specific demographics or regions if the user base is diverse.
  - Trend Score: A time-weighted metric that emphasizes recent engagement, used for trending content.

3. Contextual Features

- Time and Day:
  - Time of Day: Include features for the current time, such as morning, afternoon, evening, and night (could be one-hot encoded).
  - Day of the Week: Encode the current day, as user engagement may differ across days (weekdays vs. weekends).

    - Season or Event Indicator: For special events or seasons (e.g., holiday season), use binary features to indicate if a specific period applies to the current time.
- Device and Platform Features:
    - Device Type: Encode whether the user is on mobile, desktop, or tablet.
    - App vs. Web: Capture the platform type to adjust the type of recommended content (app users may engage differently than web users).
- Location Context:
    - Geolocation (City, Region): Use one-hot encoding or embeddings to capture the user's location.
    - Weather Features: Add features like temperature or weather conditions if location data is available, as weather may influence content preferences.

4. Feedback and Real-Time Features

- Recent Engagement Indicators:
    - Session-Based Engagement: Capture engagement metrics for the current session (e.g., number of clicks so far, time spent).
    - Previous Article Engagement: For the latest articles the user interacted with, create features indicating topic, sentiment, and engagement to tailor the next recommendations.
- Feedback Signals:
    - Explicit Feedback: Features that capture explicit user feedback (e.g., ratings, thumbs up/down).
    - Negative Interaction Signals: Track actions like hiding posts or marking content as irrelevant to avoid recommending similar items.

5. External Data Features

- Trending Topics (External Source): Include external trending data (e.g., from social media) to boost content related to trending topics in recommendations.
- Sentiment Trends: Use overall sentiment trends for a topic or region, which may help align with current user mood or preferences.

Post Features

Each post can have several features that contribute to its representation in the system, such as:

- **Content Type**: Whether the post is a text update, image, video, or link.

- **Engagement Metrics**: Likes, shares, comments, and views that indicate how popular or engaging a post is.
- **Metadata**: Information about the post, such as the time of posting, location tags, and hashtags.

User:

ID, username Demographics (Age, gender, location) Context (device, time of day, etc) Interaction history (e.g. user click rate, total clicks, likes, etc)

- User-Post interaction:
  - IDs (user, Ad), interaction type, time, location

<u>Model Selection:</u>

1. Collaborative Filtering

- Pros: Learns from user-item interactions, capturing latent patterns in user preferences without needing content data.
- Cons: Suffers from the "cold start" problem for new users and new content. Limited if users don't have a lot of interaction history.
- Implementation: Matrix factorization models like SVD or neural approaches like Neural Collaborative Filtering (NCF) can be used to predict user-item affinity. NCF can capture more complex patterns than traditional matrix factorization.

2. Content-Based Filtering

- Pros: Works well for new or niche content by analyzing the content itself. Can recommend relevant items even if the user is new, as long as we have their initial preferences.
- Cons: Limited personalization since it relies on the user's profile and may over-recommend similar items, lacking diversity.
- Implementation: Content embeddings (e.g., BERT embeddings for text) are used to represent articles, and cosine similarity or other distance metrics can recommend items with similar features.

3. Hybrid Models

- Pros: Combines the strengths of collaborative and content-based filtering, improving personalization and handling both cold start (content-based part) and diversity (collaborative part).
- Cons: Higher complexity and requires careful tuning to balance both methods. Computationally more intensive.

- Implementation: Use collaborative filtering as the base, with content-based recommendations added when the user-item interaction is sparse. Methods like weighted hybrid or model-based hybrid combine predictions from both models.

4. Multi-Task Learning Models

- Pros: Can optimize for multiple signals simultaneously (e.g., clicks, shares, dwell time), potentially providing more holistic and engaging recommendations.
- Cons: More complex to train and requires labeled data for each task. Also, challenging to balance all signals effectively.
- Implementation: Use deep learning architectures with shared layers and separate heads for each task (e.g., clicks, shares, etc.), enabling the model to capture patterns that benefit multiple engagement metrics.

Generating Candidate Posts

The first step is to identify the pool of posts available for each user. This pool consists of various content types that users might interact with, including:

- **User Posts**: Posts made by friends, followed pages, or groups the user is part of.
- **Sponsored Content**: Ads targeted to users based on their interests and demographics.
- **Shared Content**: Posts shared by users' connections. Posts in which friends are tagged.
- **Trending Topics**: Popular content that may not be directly related to a user's connections but is gaining traction.
- **Filtering Mechanism**: Apply filtering to ensure diversity in the candidate set. This might include:
  - **Diversity Constraints**: Ensuring that the recommended posts come from a variety of sources (friends, pages, groups).
  - **Recency Filtering**: Prioritizing more recent posts to keep content fresh and relevant.
- **Candidate Set Formation**: The result is a diverse set of posts that reflect both the user's preferences and interests, as well as the popularity and recency of the content.

Preparing for the Ranking Model

After generating the candidate set, the next phase is to pass these candidates to the ranking model. Key aspects of this phase include:

- **Feature Engineering for Ranking**: Creating additional features that can enhance the ranking process, such as:
  - **Engagement Probability**: Predicting the likelihood of a user engaging with a post based on historical interaction patterns.

- **Post Quality Score**: A score that may incorporate factors such as engagement metrics and content quality.

We choose NN

- unstructured data (text, img, video)
- embedding layers for categorical features
- fine tune pre-trained models used for feat eng.

multi-labels: P(click), P(like), P(Share), P(comment)

- Loss function:
  - L = sum of L_is for each task
  - for binary classif tasks: CE
  - for regression task: MAE, MSE, or Huber loss

Multi-Task Learning Model Design

A multi-task learning model optimizes for multiple engagement signals (e.g., clicks, shares, dwell time), aiming to balance these objectives for more holistic recommendations.

Task-Specific Heads:

- Each task represents a different user engagement signal (e.g., clicks, shares, dwell time).
- Loss Functions: Use different loss functions for each head (e.g., cross-entropy for clicks/shares, mean squared error for dwell time), with weights to balance each task's importance.

c. Training:

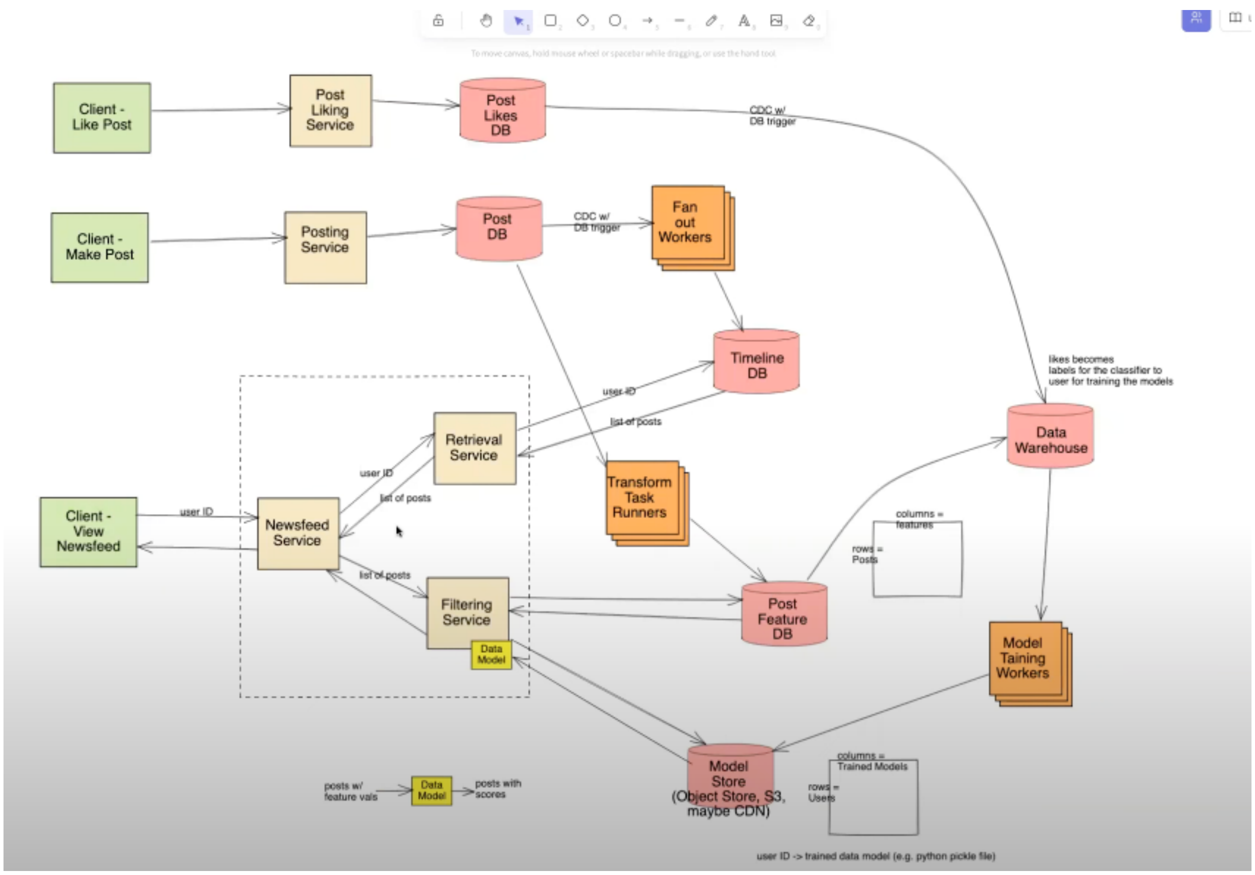
- Train the model jointly on all tasks by minimizing a weighted sum of the individual losses for each task. This enables the shared embedding layers to learn representations that are useful across tasks, while each task-specific head fine-tunes for its respective signal.
- Adjust task weights based on business priorities or model performance on each task.

Output: The model outputs separate predictions for each engagement metric, which can then be combined into an overall relevance score.

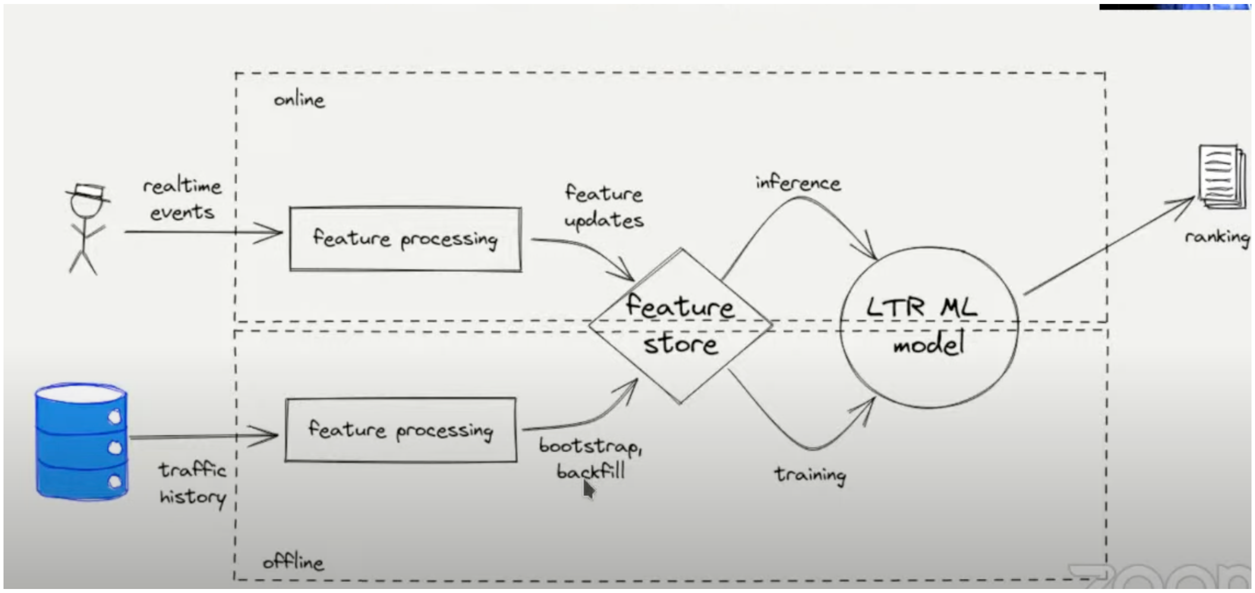
Evaluation Metrics

1. Offline Metrics:
   - Precision, Recall, F1 Score: For testing accuracy in recommending relevant items.
   - NDCG (Normalized Discounted Cumulative Gain): To evaluate ranking quality based on user engagement.
   - Coverage: Ensuring diverse recommendations across categories.

2. Online Metrics:
    - CTR: The click-through rate on recommended items.
    - Dwell Time: Measures user engagement with recommended articles.
    - Conversion Rate: Clicks or engagements that lead to subscriptions or further actions.
    - Bounce Rate: Lowering the rate can indicate higher relevance.



https://www.youtube.com/watch?v=JiGrpySlVA0&list=PLlvnxKilk3aKx0oFua-HTtFf-d_inQ8Qn&index=9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