# COMP9727: Recommender Systems

## Lecture 8: Contextual Recommendation

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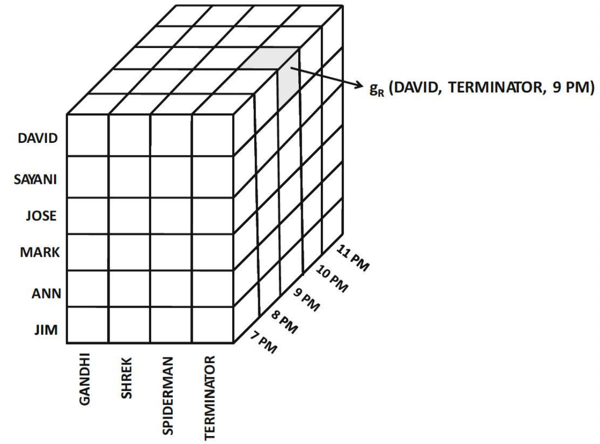
# This Lecture

- Context
  - Ubiquitous Computing Environments
  - Pervasive Computing/Wearable Devices
  - Group Recommendation
- Application Areas
  - Location-Aware Recommender Systems (Mobile Commerce)
  - Smart Homes/Cities (Healthcare, Planning)
  - Virtual/Augmented Reality (Tourism, Museums, Shopping)
- Techniques
  - Factorization Machines
  - Large Language Models



# Context in Ratings



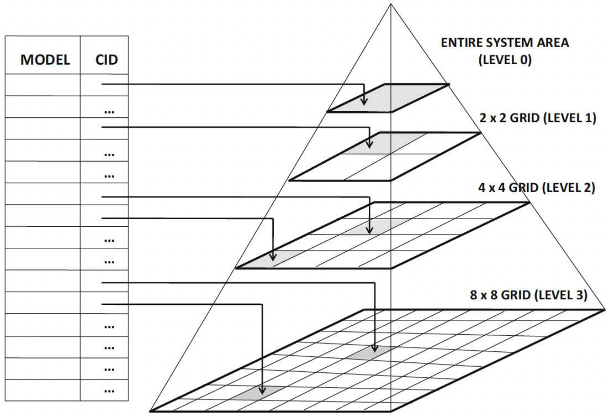


# Pre- and Post-Filtering

- Arbitrary context features
  - e.g. location, time, companions, holiday?, ...
- Pre-filtering
  - Learn model using only context-relevant data (more sparse)
- Post-filtering
  - Generate candidates as normal, then filter/reweight by context
  - Multiply ratings by $P(u,i,C)$ found using content-based methods
  - Learn $P(u,i,C)$ from all users, e.g. $P(\text{comedy}|\text{weekend})$
  - ... or from just the similar users to $u$, depending on $C$

# Location Hierarchy








# Pairwise Interaction Tensor Factorization

- MF: Factorize ratings matrix $R = UV^T$
  - $R$ is $m \times n$, $U$ is $m \times k$, $V$ is $n \times k$
  - Estimate $\hat{r}_{ij} = u_i \cdot v_j$ = sum of $u_{ik}.v_{jk}$ over all the factors $k$
- PITF: Factorize ratings tensor $R = UV^T + VW^T + UW^T$
  - $R$ is $m \times n$, $U$ is $m \times k$, $V$ is $n \times k$, $W$ is $d \times k$
  - Estimate $\hat{r}_{ijc} = u_i \cdot v_j + v_j \cdot w_c + u_i \cdot w_c$
  - Solve optimization problem using Stochastic Gradient Descent
  - Simple generalization of MF that works well with sparse data





# Factorization Machines

Matrix Factorization Training Data

| | $i_1$ | $i_2$ | $i_3$ |
|---|---|---|---|
| $u_1$ | 2 | 4 | |
| $u_2$ | | 1 | |
| $u_3$ | 3 | | 5 |

Factorization Machine Training Data

| | $u_1$ | $u_2$ | $u_3$ | $i_1$ | $i_2$ | $i_3$ | $a_1$ | $a_2$ | $y$ |
|---|---|---|---|---|---|---|---|---|---|
| $x_1$ | 1 | 0 | 0 | 1 | 0 | 0 | 2.0 | 0.0 | 2 |
| $x_2$ | 1 | 0 | 0 | 0 | 1 | 0 | 1.5 | 0.5 | 4 |
| $x_3$ | 0 | 1 | 0 | 0 | 1 | 0 | 0.0 | 1.0 | 1 |
| $x_4$ | 0 | 0 | 1 | 1 | 0 | 0 | 0.3 | 0.7 | 3 |
| $x_5$ | 0 | 0 | 1 | 0 | 0 | 1 | 3.2 | 1.7 | 5 |

Users — Items — Auxiliary Features — Observed Ratings

Problem: Very very sparse matrix





# Factorization Machines

- Number of input variables is $p = m + n + d$
- Assume one factor vector $\vec{v}_i$ of length $k$ for each input variable $x_i$
- Estimate $\hat{y}(\vec{x}) = g + \sum_{i=1}^{p} b_i x_i + \sum_{i=1}^{p} \sum_{j=i+1}^{p} (\vec{v}_i \cdot \vec{v}_j) x_i x_j$
- Most of the $x_i$ and $x_j$ are 0, hence most of the $x_i x_j$ are 0
- Solve optimization problem using Stochastic Gradient Descent
  - Update $\theta \leftarrow \theta(1 - \alpha\lambda) + \alpha e(\vec{x}) \frac{\partial \hat{y}(\vec{x})}{\partial \theta}$ where $e(\vec{x}) = y(\vec{x}) - \hat{y}(\vec{x})$, $\alpha$ is the learning rate and $\lambda$ is the regularization parameter

$$\frac{\partial \hat{y}(\vec{x})}{\partial \theta} = \begin{cases} 1 & \text{if } \theta \text{ is } g \\ x_i & \text{if } \theta \text{ is } b_i \\ x_i \sum_{j=1}^{p} v_{jk} x_j - v_{ik} x_i^2 & \text{if } \theta \text{ is } v_{ik} \end{cases}$$

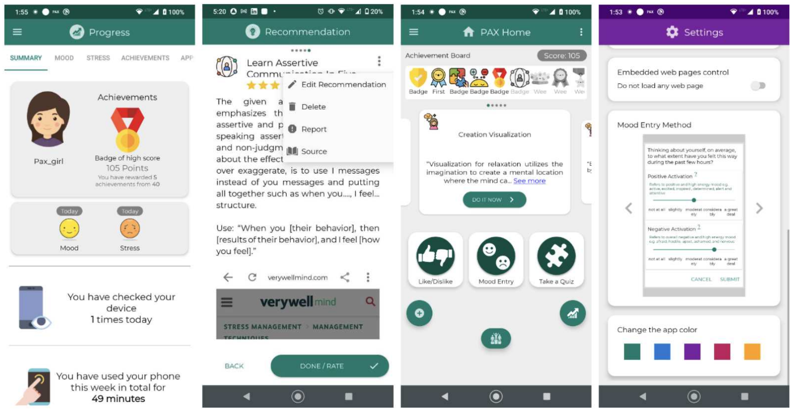
# Mobile Commerce







# Persuasive Technology in Mobile Health

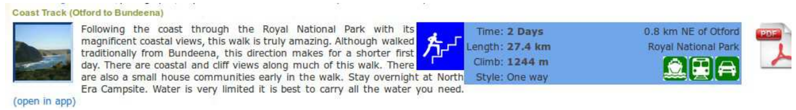








# Group-Based Hike Recommender




- Activity (e.g. climbing), distance, time, elevation, steps, incline
- Context: Weather, accessibility, hazards
- Fitness of the hiker(s) – aim to learn from past activity





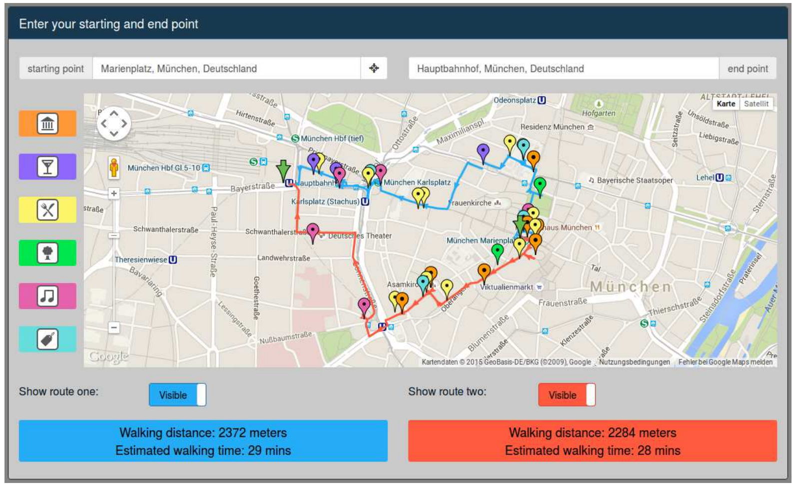

# Smart Cities

# Point-of-Interest CF Recommendation





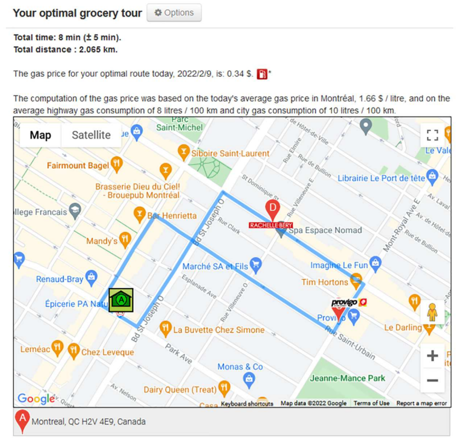

# POI Content-Based Recommendation








# Shopping Tour Recommendation

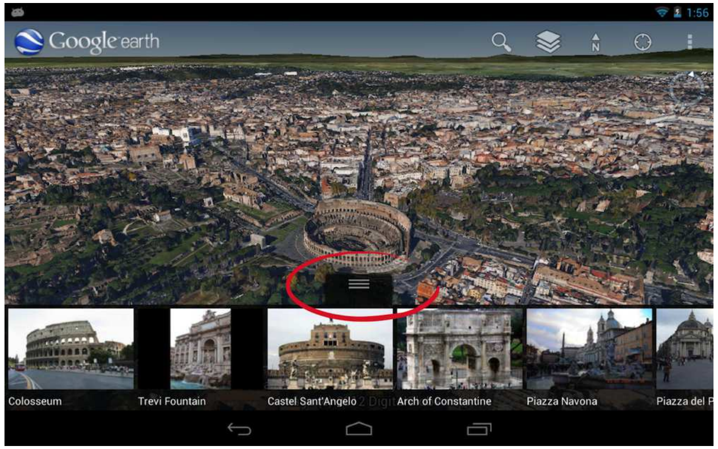



An example of optimal real-time shopping path available on the MyGroceryTour platform (screenshot taken from: http://www.mygrocerytour.com)

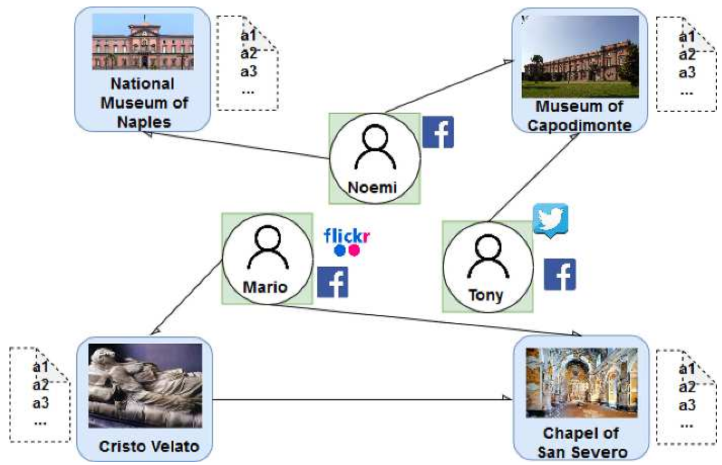




# Google Tour Guide



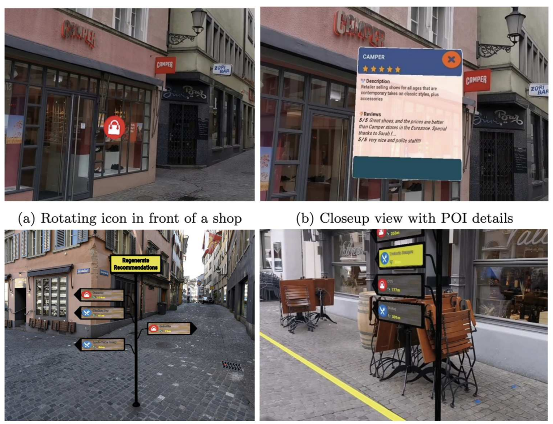
# Google Tour Guide Data





# Augmented Reality City Tour



(a) Rotating icon in front of a shop (b) Closeup view with POI details

(c) Signpost with POI recommendations (d) Path to a suggested POI

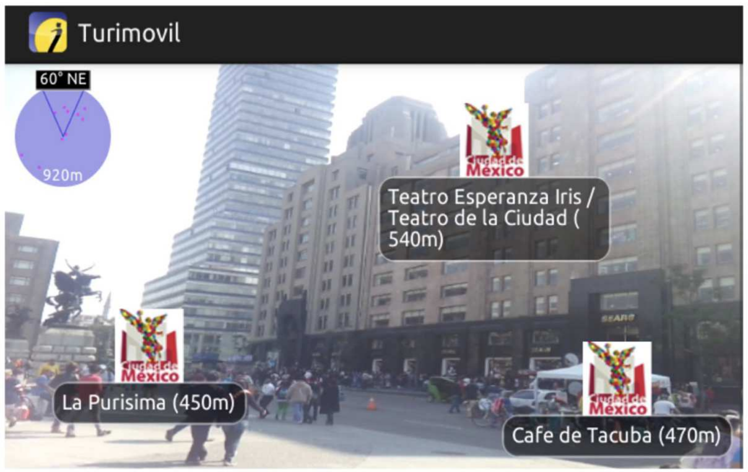


# Augmented Reality Museum Visit

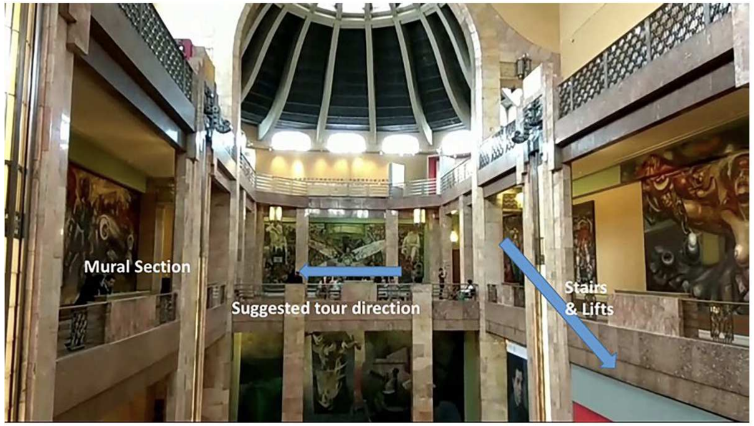


# Augmented Reality Museum Visit



# Augmented Reality Museum Visit









# Augmented Reality Museum Visit







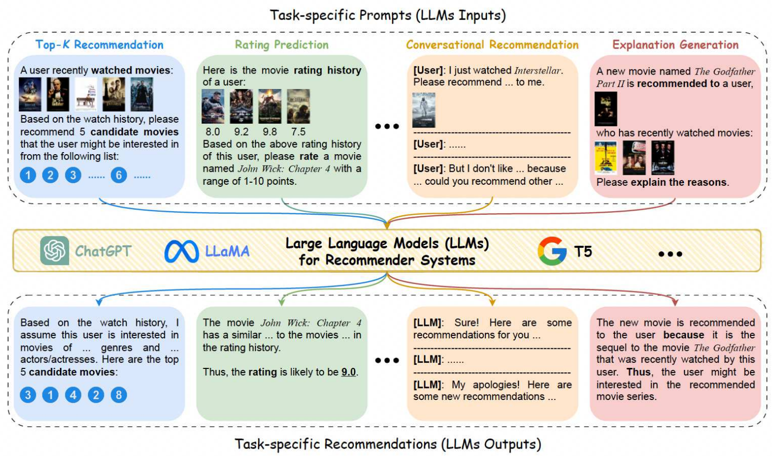
# Recommendation in Virtual Commerce

- Determine preferred viewpoint from user interactions
- Extract of item for matching and background colour
- Recommend similar items using "style" tags
- Replace existing item in image by recommended item



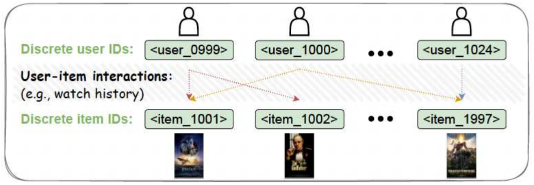



# LLM for Recommender Systems

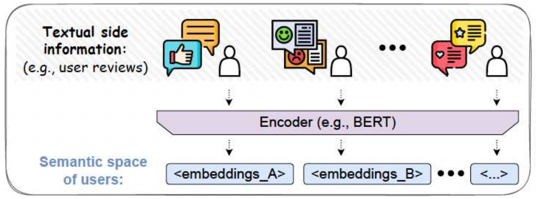


# LLM Representations

- ID-Based Representation



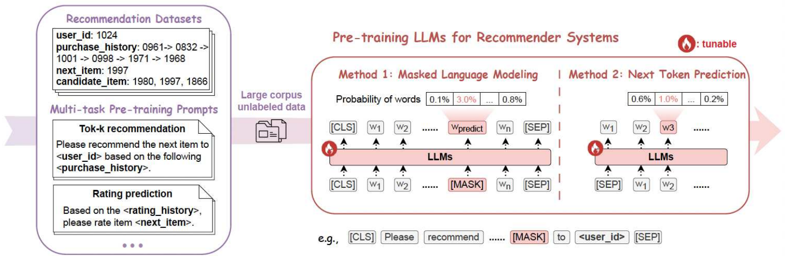

- Textual Side Information Enhanced Representation

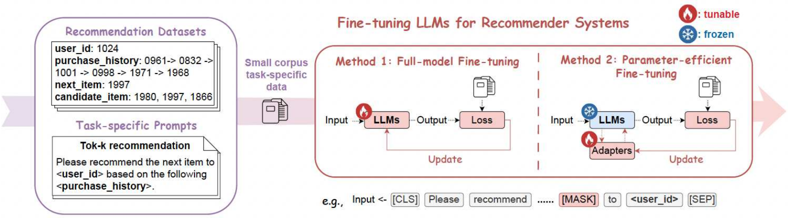







# LLM Pretraining and Fine-Tuning

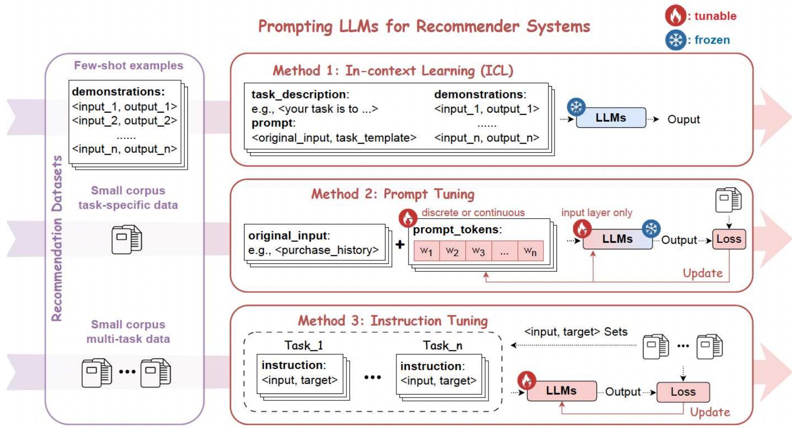







# LLM Prompting








# Summary

- Lot of software engineering surrounding recommender systems
- Context generalizes user-generated tags and temporal features
- Can apply content-based, CF and hybrid methods
- Effectiveness of methods depends heavily on availability of data
  - Not just quantity, but quality
- Can exploit data from body sensors, Internet of Things, etc.
- Lot of talk about recommendation in smart environments
- Not really sure about virtual/augmented reality, the “metaverse”, etc.
- LLMs more about potential approaches at this stage, no real results