COMP9727: Recommender Systems

Lecture 1: Introduction

Wayne Wobcke

e-mail:w.wobcke@unsw.edu.au

About Me: Recommender Systems Work

- Personal Assistants
  - E-Mail Management Assistant (recommend folders)
  - Dialogue Assistant (tailor interaction to users)
  - Calendar Assistant (suggest task/activity times)
  - Multi-Agent Meeting Scheduling (suggest meeting times)
- Recommender Systems
  - Conversational recommender system for cars
  - People-to-people recommender system for online dating
  - Job recommender system based on career progression
- Event Extraction
  - Recommend events “of interest” from news, social media
  - Recommend events with high likelihood of violence

This Lecture

- Application Areas for Recommender Systems
- Overview of Technical Approaches
- Recommender Systems Issues
- User Interface Design Issues for Recommender Systems
- Business Models for Recommender Systems
- Evaluation of Recommender Systems

Application Areas

- News: Google, Facebook, Apple, etc.
- Social Media Feeds: Facebook, Instagram, WeChat, X, Weibo, etc.
- Music: Spotify, Apple Music, etc.
- Movies/TV/Videos: IMDb, Netflix, YouTube, TikTok, etc.
- Consumer Goods: Amazon, eBay, Taobao, JD.com, etc.
- Hotels: Booking.com, Expedia, TripAdvisor, Airbnb, etc.
- Restaurants: Yelp, Google, etc.
- Rideshare: Uber, Lyft, etc.
- People: Facebook, RSVP, OkCupid, eHarmony, etc.
- + Jobs, Meals, Video Games, Cars, Houses, Tourist Attractions, etc.

Search vs Recommendation

- Search
  - User initiated from search query
  - Gives same results and ranking (... though Google?)
- Recommendation
  - May not be initiated by explicit user request
  - Results are personalized, depending on:
    - User “profile” of interests – content-based
    - User (session) history of system interactions
    - Activity of “similar” users – collaborative filtering
    - A combination of the above in a machine learning model

Broad Technical Approaches

- Content-Based Recommendation
  - News, Research Articles, Meals, Hotels, Restaurants, etc.
- Collaborative Filtering (CF)
  - Music, Movies/TV/Videos, Consumer Goods, etc.
- Knowledge-Based Recommender Systems
  - Cars, Houses/Apartments, Cameras, etc.
- Sequential Recommender Systems
  - e.g. recommend movies based on previous movies watched
- Context-Aware Recommender Systems
  - e.g. recommend music based on time of day, mood, emotion

Content-Based Recommendation

Useful when items can easily be categorized

- Categorize items using a predefined(?) ontology?
- Build user profile of interests using the same ontology
- Recommend items based on “similarity” between item and profile

Data sources: Explicit user interests, user–system interactions

Many ways to define “similarity”

Problems with Profiles

Example: News Articles

- Lack of novelty: recommended items tend to be very similar
- Echo chambers: user sees only articles with same point of view
- Lack of precision: profiles too coarse if categories are broad
- Updating profiles: user interests change over time
- Balance: short-term vs long-term interests
- Ambiguity: e.g. “Big Bang Theory”

Collaborative Filtering

Useful when items cannot easily be categorized

- Item-based: Recommend items “similar” to those consumed
  - Amazon: Items are “similar” if users bought them together
  - Users who bought this also bought that
- User-based: Recommend items consumed by “similar” users
  - Users are “similar” if they rated the same items similarly
  - You might like this other item liked by those users

Data sources: Explicit ratings, user–system interactions

Many ways to define “similarity” of users/items

Problems with (Movie) Ratings

- Meaning of scale changes over time: “uberization”
- Individual differences in rating interpretation
- Sparsity: users rate few movies so few ratings overall
- Biased towards popular movies: many ratings
- Biased against “bad” movies: users don’t rate them
- New movies rated more highly: novelty factor!
- New users rate movies more highly: inexperience?
- Biased towards frequent raters: e.g. teenagers?
- Biased towards English language movies: more users
- Astroturfing: Fake reviews and ratings

Recommender Systems Issues

- Cold start problems: users and items
- Over-recommendation of popular items
- Users with obscure tastes
- The “long tail”: 80/20 rule
- Diversity of recommendations
- Serendipity: discovery of genuinely new items
- Transparency of recommendations(?)
- Explainability of recommendations(?)
- Legal regulations: e.g. financial, medical advice
- Polarization: users only see extremes of an argument

Knowledge-Based Recommender Systems

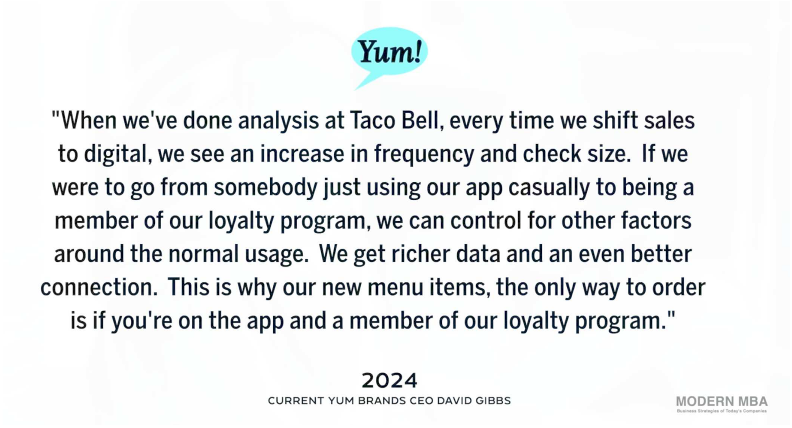
Useful when users don’t know exactly what they want

- Also known as “conversational” recommender systems
- Users cannot articulate their needs as a search query
- Suitable for casual and naive users, for infrequent purchases
- Start with a single example then provide “critiques”
- Helps users navigate a complex search space
- Helps users understand tradeoffs in a complex domain
- Users learn their preferences during search
- Functions as a decision-support tool
- Based on consumer buying behaviour models

User Modelling and Personalization

- How to model users: “user profile”
- How to get data about users: clicks, likes, purchases, etc.
- How reliable is the data: e.g. watching vs rating a movie
- How to model changes in user interests: dynamics
- How to balance long-term and short-term interests
- Basis of recommendation: profile, session, etc.
- Can users be “clustered” into groups?
- Ethical/legal concern of data privacy

Let the Data Speak for Itself ...



Yum!

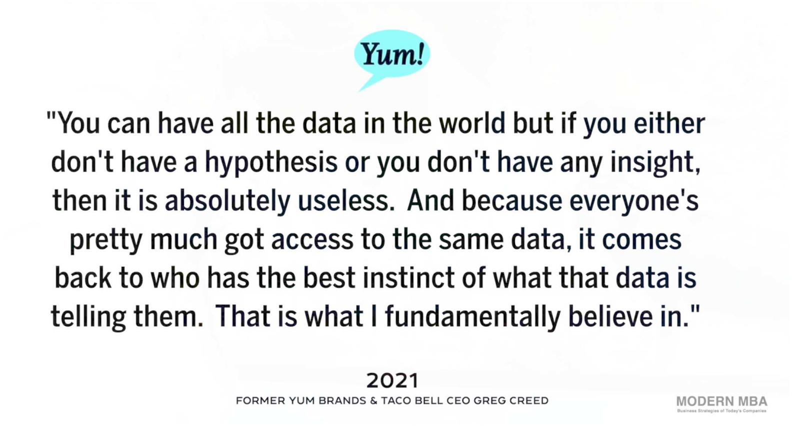
"When we've done analysis at Taco Bell, every time we shift sales to digital, we see an increase in frequency and check size. If we were to go from somebody just using our app casually to being a member of our loyalty program, we can control for other factors around the normal usage. We get richer data and an even better connection. This is why our new menu items, the only way to order is if you're on the app and a member of our loyalty program."

2024

CURRENT YUM BRANDS CEO DAVID GIBBS

MODERN MBA

But What is It Saying?



Yum!

"You can have all the data in the world but if you either don't have a hypothesis or you don't have any insight, then it is absolutely useless. And because everyone's pretty much got access to the same data, it comes back to who has the best instinct of what that data is telling them. That is what I fundamentally believe in."

2021

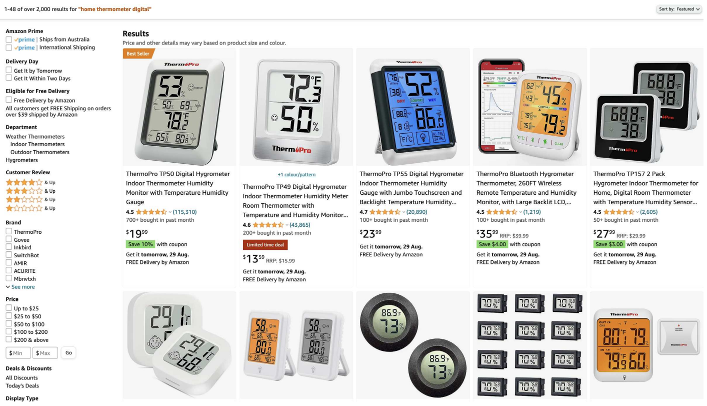
FORMER YUM BRANDS & TACO BELL CEO GREG CREED

MODERN MBA

User Interface Design Issues

- How many recommendations to give at one time
- How and where on the screen to display them
- How to describe the recommendations: “suggestions”?
- How to get user feedback (non-intrusively)
- How to get useful feedback (especially dislikes)
- How to use user feedback (in real-time?)
- When to give (and change) recommendations
- How not to annoy the user so they will come back

Amazon Search Results



1-48 of over 2,000 results for "home thermometer digital"

Sort by: Featured

Amazon Prime
☐ prime | Ships from Australia
☐ prime | International Shipping

Delivery Day
☐ Get It by Tomorrow
☐ Get It Within Two Days

Eligible for Free Delivery
☐ Free Delivery by Amazon
All customers get FREE Shipping on orders over $39 shipped by Amazon

Department
Weather Thermometers
Indoor Thermometers
Outdoor Thermometers
Hygrometers

Customer Review
& Up
& Up
& Up
& Up

Brand
☐ ThermoPro
☐ Govee
☐ Inkbird
☐ SwitchBot
☐ AMIR
☐ ACURITE
☐ Mbnvtxh
See more

Price
☐ Up to $25
☐ $25 to $50
☐ $50 to $100
☐ $100 to $200
☐ $200 & above
$Min $Max Go

Deals & Discounts
All Discounts
Today's Deals

Display Type

Results
Price and other details may vary based on product size and colour.

Best Seller
ThermoPro TP50 Digital Hygrometer Indoor Thermometer Humidity Monitor with Temperature Humidity Gauge
4.5 (115,310)
700+ bought in past month
$19.99
Save 10% with coupon
Get it **tomorrow, 29 Aug.**
FREE Delivery by Amazon

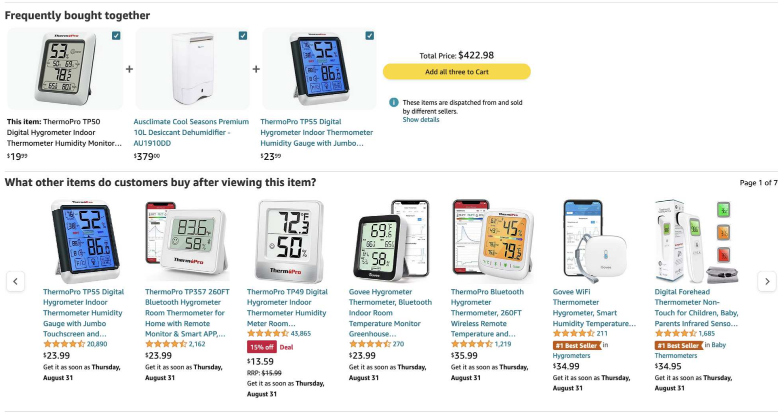
+1 colour/pattern
ThermoPro TP49 Digital Hygrometer Indoor Thermometer Humidity Meter Room Thermometer with Temperature and Humidity Monitor...
4.6 (43,865)
200+ bought in past month
Limited time deal
$13.59 RRP: ~~$15.99~~
Get it **tomorrow, 29 Aug.**
FREE Delivery by Amazon

ThermoPro TP55 Digital Hygrometer Indoor Thermometer Humidity Gauge with Jumbo Touchscreen and Backlight Temperature Humidity...
4.7 (20,890)
100+ bought in past month
$23.99
Get it **tomorrow, 29 Aug.**
FREE Delivery by Amazon

ThermoPro Bluetooth Hygrometer Thermometer, 260FT Wireless Remote Temperature and Humidity Monitor, with Large Backlit LCD,...
4.5 (1,219)
100+ bought in past month
$35.99 RRP: ~~$39.99~~
Save $4.00 with coupon
Get it **tomorrow, 29 Aug.**
FREE Delivery by Amazon

ThermoPro TP157 2 Pack Hygrometer Indoor Thermometer for Home, Digital Room Thermometer with Temperature Humidity Sensor...
4.5 (2,605)
50+ bought in past month
$27.99 RRP: ~~$29.99~~
Save $3.00 with coupon
Get it **tomorrow, 29 Aug.**
FREE Delivery by Amazon

Amazon Recommendations



Frequently bought together

☑ **This item:** ThermoPro TP50 Digital Hygrometer Indoor Thermometer Humidity Monitor…
$19.99

☑ Ausclimate Cool Seasons Premium 10L Desiccant Dehumidifier - AU1910DD
$379.00

☑ ThermoPro TP55 Digital Hygrometer Indoor Thermometer Humidity Gauge with Jumbo…
$23.99

Total Price: $422.98
Add all three to Cart
These items are dispatched from and sold by different sellers.
Show details

What other items do customers buy after viewing this item?

Page 1 of 7

ThermoPro TP55 Digital Hygrometer Indoor Thermometer Humidity Gauge with Jumbo Touchscreen and…
20,890
$23.99
Get it as soon as **Thursday, August 31**

ThermoPro TP357 260FT Bluetooth Hygrometer Room Thermometer for Home with Remote Monitor & Smart APP,…
2,162
$23.99
Get it as soon as **Thursday, August 31**

ThermoPro TP49 Digital Hygrometer Indoor Thermometer Humidity Meter Room…
43,865
15% off Deal
$13.59
RRP: ~~$15.99~~
Get it as soon as **Thursday, August 31**

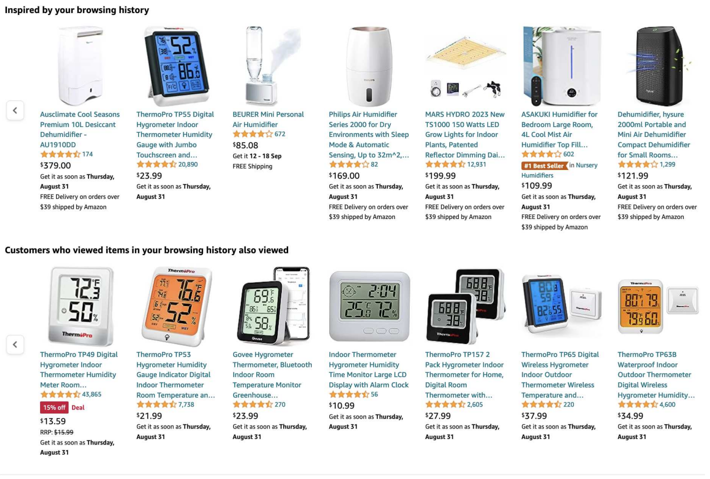
Govee Hygrometer Thermometer, Bluetooth Indoor Room Temperature Monitor Greenhouse…
270
$23.99
Get it as soon as **Thursday, August 31**

ThermoPro Bluetooth Hygrometer Thermometer, 260FT Wireless Remote Temperature and…
1,219
$35.99
Get it as soon as **Thursday, August 31**

Govee WiFi Thermometer Hygrometer, Smart Humidity Temperature…
211
#1 Best Seller in Hygrometers
$34.99
Get it as soon as **Thursday, August 31**

Digital Forehead Thermometer Non-Touch for Children, Baby, Parents Infrared Senso…
1,685
#1 Best Seller in Baby Thermometers
$34.95
Get it as soon as **Thursday, August 31**

Amazon Recommendations



Inspired by your browsing history

Ausclimate Cool Seasons Premium 10L Desiccant Dehumidifier - AU1910DD
174
$379.00
Get it as soon as **Thursday, August 31**
FREE Delivery on orders over $39 shipped by Amazon

ThermoPro TP55 Digital Hygrometer Indoor Thermometer Humidity Gauge with Jumbo Touchscreen and…
20,890
$23.99
Get it as soon as **Thursday, August 31**

BEURER Mini Personal Air Humidifier
672
$85.08
Get it **12 - 18 Sep**
FREE Shipping

Philips Air Humidifier Series 2000 for Dry Environments with Sleep Mode & Automatic Sensing, Up to 32m^2,…
82
$169.00
Get it as soon as **Thursday, August 31**
FREE Delivery on orders over $39 shipped by Amazon

MARS HYDRO 2023 New TS1000 150 Watts LED Grow Lights for Indoor Plants, Patented Reflector Dimming Dai…
12,931
$199.99
Get it as soon as **Thursday, August 31**
FREE Delivery on orders over $39 shipped by Amazon

ASAKUKI Humidifier for Bedroom Large Room, 4L Cool Mist Air Humidifier Top Fill…
602
#1 Best Seller in Nursery Humidifiers
$109.99
Get it as soon as **Thursday, August 31**
FREE Delivery on orders over $39 shipped by Amazon

Dehumidifier, hysure 2000ml Portable and Mini Air Dehumidifier Compact Dehumidifier for Small Rooms…
1,299
$121.99
Get it as soon as **Thursday, August 31**
FREE Delivery on orders over $39 shipped by Amazon

Customers who viewed items in your browsing history also viewed

ThermoPro TP49 Digital Hygrometer Indoor Thermometer Humidity Meter Room…
43,865
15% off Deal
$13.59
RRP: ~~$15.99~~
Get it as soon as **Thursday, August 31**

ThermoPro TP53 Hygrometer Humidity Gauge Indicator Digital Indoor Thermometer Room Temperature an…
7,738
$21.99
Get it as soon as **Thursday, August 31**

Govee Hygrometer Thermometer, Bluetooth Indoor Room Temperature Monitor Greenhouse…
270
$23.99
Get it as soon as **Thursday, August 31**

Indoor Thermometer Hygrometer Humidity Time Monitor Large LCD Display with Alarm Clock
56
$10.99
Get it as soon as **Thursday, August 31**

ThermoPro TP157 2 Pack Hygrometer Indoor Thermometer for Home, Digital Room Thermometer with…
2,605
$27.99
Get it as soon as **Thursday, August 31**

ThermoPro TP65 Digital Wireless Hygrometer Indoor Outdoor Thermometer Wireless Temperature and…
220
$37.99
Get it as soon as **Thursday, August 31**

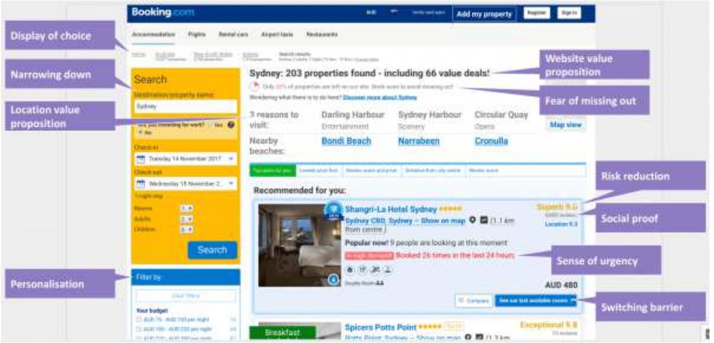
ThermoPro TP63B Waterproof Indoor Outdoor Thermometer Digital Wireless Hygrometer Humidity…
4,600
$34.99
Get it as soon as **Thursday, August 31**

Business Models

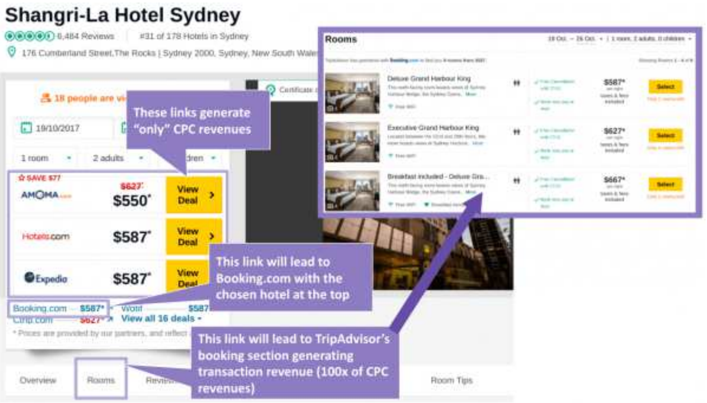
Examples: Booking.com, Expedia, TripAdvisor

- Booking.com (US$112 Billion)
  - Commission model – Cut from actual bookings
- Expedia (US$15 Billion)
  - Merchant model – Buy rooms in bulk and resell
- TripAdvisor (US$2 Billion)
  - Click-through advertising – Paid per view (cents per mille)

Booking.com



TripAdvisor

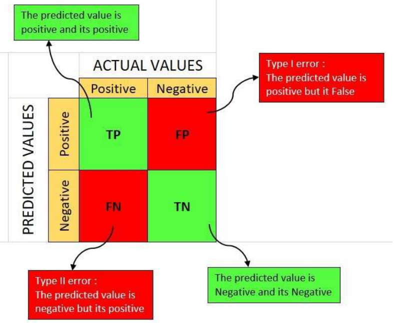

Shangri-La Hotel Sydney
6,484 Reviews
#31 of 178 Hotels in Sydney
176 Cumberland Street,The Rocks | Sydney 2000, Sydney, New South Wales
Rooms
These links generate "only" CPC revenues
This link will lead to Booking.com with the chosen hotel at the top
This link will lead to TripAdvisor's booking section generating transaction revenue (100x of CPC revenues)
$550
$587
$587
View Deal
View all 16 deals
Overview
Rooms
Room Tips

Evaluation of Recommender Systems

- Historical data analysis
  - Often this is all we have . . . until deployment
  - Predict user actions (but without the recommender)
- User studies
  - Informal: 5–10 people for feedback (but often just on the UI)
  - Formal: A/B testing to compare different versions of the system

Metrics: Precision and Recall

When you have exactly one positive class (e.g. movies user likes)


The predicted value is positive and its positive
ACTUAL VALUES
Positive
Negative
PREDICTED VALUES
Positive
Negative
TP
FP
FN
TN
Type I error : The predicted value is positive but it False
Type II error : The predicted value is negative but its positive
The predicted value is Negative and its Negative

Precision = TP/(TP+FP) = TP/(Predicted Positive)
Recall = TP/(TP+FN) = TP/(Actual Positive)

Metrics: Precision and Recall

Still with exactly one positive class

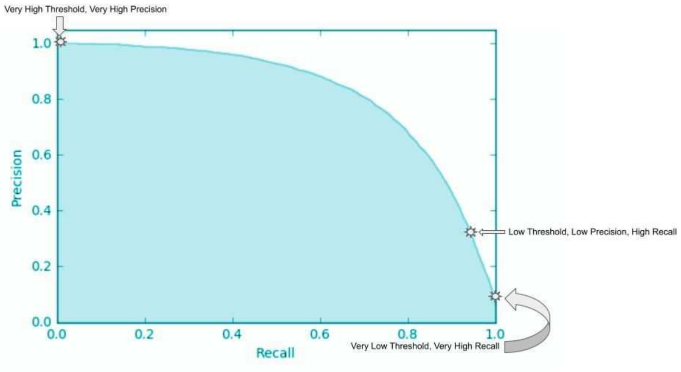
- Precision (P) = TP/(TP+FP) – you want what you get
- Recall (R) = TP/(TP+FN) – you get what you want
- F1 = 2PR/(P+R) – harmonic mean of precision and recall
- Accuracy = (TP+TN)/(Whole Dataset)

Suppose recommendations are ranked and look only at top-N

- Precision@N = (TP in top-N)/N – precision over top-N
- Recall@N = (TP in top-N)/(Actual Positive) – this will be small

Precision-Recall Curve

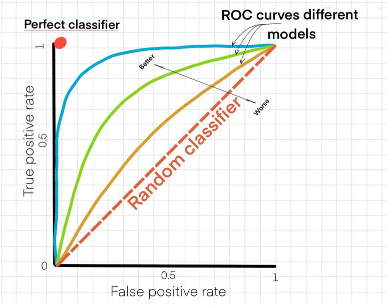
Still with exactly one positive class



Tradeoff between precision and recall; suitable when classes imbalanced

Receiver Operating Characteristic Curve

Still with exactly one positive class



True Positive Rate = Recall
False Positive Rate = FP/(Negatives)
AUC = Area Under the Curve

Tradeoff between TP and FN; suitable when classes balanced

Multiple Classes: Per-Class Metrics

$n \times n$ Confusion Matrix (each instance in one class)

	Predicted c_1	Predicted c_2	$\cdots$
Class c_1	c_{11}	c_{12}	c_{13}
Class c_2	c_{21}	c_{22}	c_{23}
$\cdots$	c_{31}	c_{32}	c_{33}

- Precision (class c_i) = $c_{ii}/\Sigma_j c_{ji}$ – add down column
  - Proportion of items predicted as c_i correctly classified (as c_i)
- Recall (class c_i) = $c_{ii}/\Sigma_j c_{ij}$ – add along row
  - Proportion of items in class c_i predicted correctly (as c_i)
- Accuracy = $\Sigma_i c_{ii}/\Sigma_i \Sigma_j c_{ij}$ – add all items in table

Multiple Classes: Micro/Macro-Averaging

n (one per class) 2×2 Contingency Tables

- Micro-average = Aggregated measure over all classes
  - micro-precision = $\Sigma_c \mathrm{TP}_c / \Sigma_c (\mathrm{TP}_c + \mathrm{FP}_c)$
  - micro-recall = $\Sigma_c \mathrm{TP}_c / \Sigma_c (\mathrm{TP}_c + \mathrm{FN}_c)$
  - Same when each instance has and is given one and only one label
  - Dominated by larger classes
- Macro-average = Average of per-class measures
  - macro-precision = $\frac{1}{n} \Sigma_c \mathrm{TP}_c / (\mathrm{TP}_c + \mathrm{FP}_c)$
  - macro-recall = $\frac{1}{n} \Sigma_c \mathrm{TP}_c / (\mathrm{TP}_c + \mathrm{FN}_c)$
  - Dominated by smaller classes
  - Useful for imbalanced classes, e.g. sentiment analysis

Metrics for Ranked Results

Suppose the ground truth data is ranked (e.g. user's rated movies) and each item i has a relevance $rel(i)$ – e.g. the rating

Let the recommender return the ranked itemlist $r_1, r_2, \cdots$

- Cumulative Gain CG@N = $\Sigma_{i=1}^{\mathrm{N}} rel(r_i)$
- Discounted Cumulative Gain DCG@N = $\Sigma_{i=1}^{\mathrm{N}} rel(r_i)/log_2(i+1)$
- Normalized DCG nDCG@N = DCG@N/(max possible DCG@N)
- Metrics for the most relevant item (hit rate, mean reciprocal rank)

Measures of closeness of ranking to ground truth relevance over top-N

Metrics for Ranked Results

Suppose the ground truth data is fully ranked (e.g. user's rated movies) and each item i has a relevance $rel(i)$ – e.g. the rating

Let the recommender return the fully ranked itemlist $r_1, r_2, \cdots$

- Item pair (i, j) is concordant if $rel(i) > rel(j)$
- Item pair (i, j) is disconcordant if $rel(i) < rel(j)$
- With N items, there are N*(N$-$1)/2 pairs
- Kendall τ_β = (Concordant $-$ Discordant)/(Number Item Pairs)
- Similar metrics for when rankings include "ties"

Measures of correlation (-1 to 1) of ranking to ground truth ranking

Metrics for Regression and Estimation

Suppose the ground truth data is numeric (e.g. user's rated movies)

Let the recommender return an estimate $\hat{r}$ for each item r (N items)

- Mean Absolute Error (MAE) = $\frac{1}{\mathrm{N}} \Sigma |\hat{r} - r|$
- Mean Squared Error (MSE) = $\frac{1}{\mathrm{N}} \Sigma (\hat{r} - r)^2$
- Root Mean Squared Error (RMSE) = $\sqrt{\frac{1}{\mathrm{N}} \Sigma (\hat{r} - r)^2}$

Measures closeness of scores to ground truth scores

Metrics for Recommender Systems

- Click-through rate
- Conversion rate
- User engagement
- Sales and revenue
- Average order value
- Customer lifetime value
- Customer retention
- Churn rate
- Coverage of item set
- Diversity: average dissimilarity of items in result sets

Problems with Metrics

- Averages don’t capture variation between users
- Metrics dominated by subgroup of highly active users
- Recommender needs to work for all users
- Need to focus on top-N metrics, but for which N?
- Need tradeoffs between multiple metrics
- Metrics tend to ignore infrequently rated long tail
- Metrics unduly influenced by outliers (some more so)
- Balance short-term revenue and long-term user experience

Evaluation Pitfalls

- Historical data analysis insufficient
  - Recommender changes behaviour: users will click differently
  - Model could be learning how the old recommender system works
  - User tastes unclear as no explicit feedback (especially negative)
  - Dynamics of users and items difficult to capture
  - Need post-deployment evaluation to confirm analysis
- Commercial feasibility
  - Gap between research and deployment environments
  - Integration with commercial systems

Course Topics

1	Introduction to Recommender Systems
2	Content-Based Recommender Systems
3	Collaborative Filtering
4	Knowledge-Based Recommender Systems
5	Social Recommender Systems
6	Social Network Recommendation
7	Sequential Recommender Systems
8	Contextual Recommender Systems
9	Machine Learning at Scale for Recommender Systems

Assessment

- Assignment
  - Week 4: Content-Based Recommender System (30%)
- Project
  - Project Pitch and Design
    - Week 5: Project Pitch (No marks)
    - Week 5: Project Design Document (20%)
  - Project Implementation and Evaluation
    - Week 10: Team Project Demonstration (30%)
    - Week 11: Individual Project Report (20%)