https://www.linkedin.com/pulse/consumer-experience-re-imagined-through-amazon-nishit-kamdar/?trackingId=mXQJvEDRTXOE8VLHhIqOfA%3D%3D

Title: Consumer Experience Re-imagined Through Personalized Recommendations

Many of today's online services use recommender systems to point their users or site visitors to additional items that might be of interest to them. Amazon's "Customers who bought . . . also bought" recommendations can be considered an extreme case of such a session-based recommendation approach. In this case, the recommendations are seemingly only dependent on the item that is currently viewed by the user (and the purchasing patterns of the community).

Customers now expect more than personal engagement, they also demand engagement at the right time, on the right device, with the right message. They also expect a true, integrated cross-channel experience.

Personalization is all about serving to Consumers individuality through modeling those complex behavioral patterns such as short-term intent and long-term taste of each individual consumers from their interaction sessions.

Physical retailers that also have an online presence and can integrate their data from all sources have a head start. It is not an easy way, as you constantly need to pivot and tweak to get the AI to work for you and meet your targeted customers' needs. But when done properly with a healthy dose of persistence, success will be yours. This leads to better engagement, retention, and long-term loyalty.

Combined with the advancement of AI-powered marketing automation platforms, extreme personalization isn't just possible, it's now emerging as a competitive advantage for modern retail brands. Now, with AI, personalization is possible for both content and context. The idea of personalization remains key to future, sustainable success.

Business Requirements

Our client is one of the large European conglomerates operating in Retail Stores, Retail Ecommerce, Hospitality and Bank businesses along with a knitting Loyalty platform.

Our client being a leading player in this space, they understand that Personalized Recommendations create significant impact in terms of the customer engagement and improving the overall lifetime value of your customers. Their business intended to understand and model their customer interactions better to serve tailored and personalized recommendations.

Proposed Solutions

At first glance, matching users to items may like sounds like a simple problem to solve. However, the task of developing an efficient recommender system is extremely challenging and complex.

Building, optimizing and deploying real-time personalization today requires specialized expertise in analytics, applied machine learning, software engineering, and systems operations. Few organizations have the knowledge, skills, budget and experience to overcome these challenges, and they often end up either abandoning the idea of using recommendation or build under-performing models.

Recommendation vs Personalization: -

Recommendations mean selecting items an individual user might be interested in. Most recommendation platforms are based on collaborative filtering technology. Recommendations algorithms build profiles for each item in terms of the most frequently viewed or purchased items when compared to other items.

Approaches for making recommendations tend to fall into one of three categories: -

- Popularity: All things being equal, recommend the most popular (or most likely to be engaged with, or most profitable) items.
- Item-based: Given an item, identify similar items (e.g., users who purchased X also purchased Y).
- User-based: Given a user's interests or past behavior, find similar users and recommend items those users have expressed interest in.

Personalization refers to customizing the user experience to the unique needs of each user including selecting appropriate content to recommend to a user (personalized recommendations), showing content that is related to a particular item and user (relevant items), reordering results to provide personalized results (personalized search), and personalized notifications/promotions (only sending relevant promotions/notification to a specific user).

AWS Personalize based Solution: -

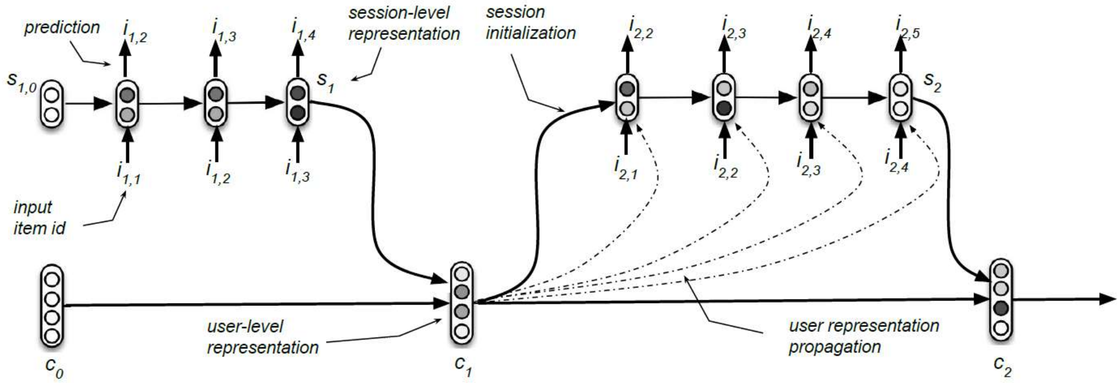
Our client happens to be an already established digital enterprise on AWS Cloud. Our goal for ML model deployment was AWS Cloud.

We explored conventional approaches of recommendation, but even advanced alternatives lacked accommodating Consumer interactions ordering.

We needed to personalize even item-2-item similarity based on user-item interactions historical data and solution should have given more importance to recent interactions.

For over 20 years, Amazon.com has built recommender systems at scale, integrating personalized recommendations across the buying experience – from product discovery to checkout. Amazon has made incredible personalization advances with its artificial intelligence, machine learning and predictive analytics and to help all the AWS customers do the same, Amazon has recently launched Amazon Personalize which is a fully-managed service that puts personalization and recommendation in the hands of developers with little or no machine learning experience.

Amazon Personalize allows the customers to create private, customized personalization recommendations that is build off of the customer data. Its underlying Deep Learning Model is the state-of-the-art Hierarchical RNN Model which helps in learning short-term intent and long-term taste of each individual consumers.

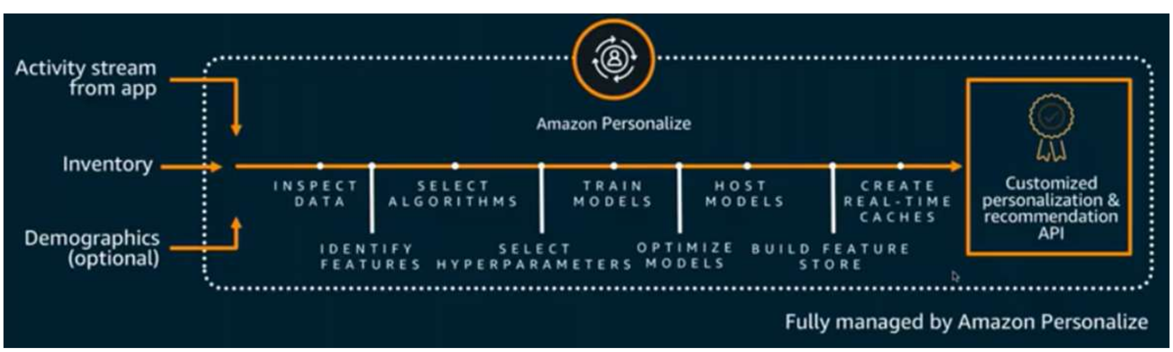


AWS Personalize model - Hierarchical RNN

Amazon Personalize supports both datasets stored in Amazon S3 and streaming data sets, e.g. events sent in real-time from a JavaScript tracker or server-side.

The conceptual workflow appears to be the following: -

The logical workflow involves several stages involving various things namely Datasets Group, Datasets, Solutions, Campaigns, etc.



- Create a *Schema* describing the *Dataset*, using Personalize-reserved keywords for User IDs, Item IDs, etc.
- Create a *Dataset Group* that contains *Datasets* used for building the model and for predicting User-Item Interactions (aka “who liked what”), Users and Items Metadata.
- Send data to *Personalize*.

- Create a *Solution*, i.e. select a recommendation recipe and train it on the Dataset Group. Below screenshot depicts the metrics score.

```
get_solution_metrics_response = personalize_client.get_solution_metrics(
    solutionVersionArn = solution_version_arn
)

print(json.dumps(get_solution_metrics_response, indent=2))
```


```
{
  "solutionVersionArn": "arn:aws:personalize:us-west-2:118541361275:solution/DEMO-solution-RetailRocket/94c516fa",
  "metrics": {
    "coverage": 0.0783,
    "mean_reciprocal_rank_at_25": 0.2325,
    "normalized_discounted_cumulative_gain_at_10": 0.2806,
    "normalized_discounted_cumulative_gain_at_25": 0.2923,
    "normalized_discounted_cumulative_gain_at_5": 0.2664,
    "precision_at_10": 0.0336,
    "precision_at_25": 0.0153,
    "precision_at_5": 0.0591
  },
```


- Create a *Campaign* to predict new samples.

```
create_campaign_response = personalize_client.create_campaign(
    name = "DEMO-campaign-RetailRocket",
    solutionVersionArn = solution_version_arn,
    minProvisionedTPS = 1
)

campaign_arn = create_campaign_response['campaignArn']
print(json.dumps(create_campaign_response, indent=2))
```


```
{
  "campaignArn": "arn:aws:personalize:us-west-2:118541361275:campaign/DEMO-campaign-RetailRocket",
  "ResponseMetadata": {
    "RequestId": "26343292-2108-41cd-97c6-78222e8f597e",
    "HTTPStatusCode": 200,
    "HTTPHeaders": {
      "content-type": "application/x-amz-json-1.1",
      "date": "Fri, 25 Oct 2019 13:34:06 GMT",
      "x-amzn-requestid": "26343292-2108-41cd-97c6-78222e8f597e",
      "content-length": "96",
      "connection": "keep-alive"
    },
    "RetryAttempts": 0
  }
}
```


- Predict personalized recommendations to Users

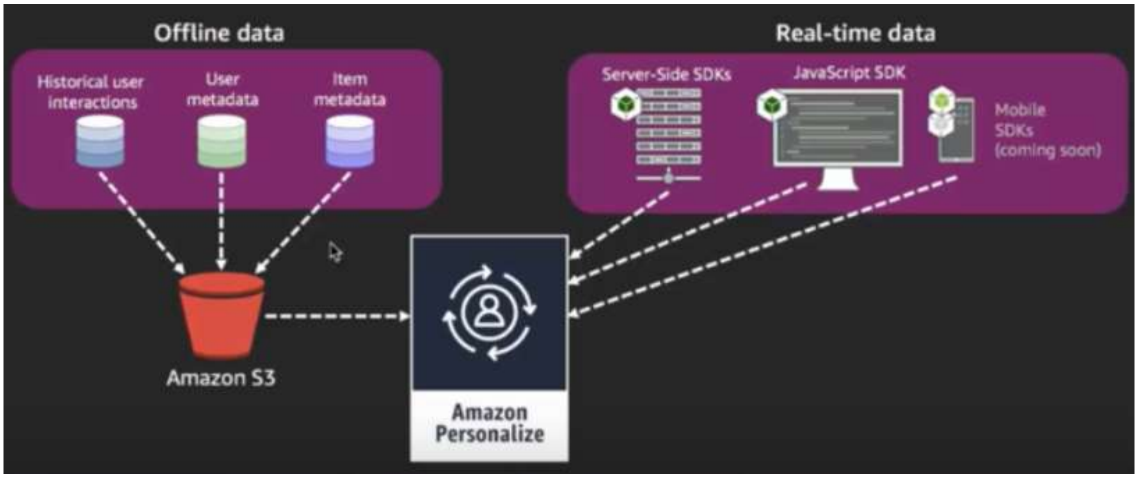
```
user_id = "599528"
item_id = "356475"
campaign_arn = "arn:aws:personalize:us-west-2:118541361275:campaign/DEMO-campaign-RetailRocket"
```

```
get_recommendations_response = personalize_runtime_client.get_recommendations(
    campaignArn = campaign_arn,
    userId = str(user_id),
    itemId = str(item_id)
)

item_list = get_recommendations_response['itemList']
item_list
```


```
[{'itemId': '453286'},
 {'itemId': '356475'},
 {'itemId': '391472'},
 {'itemId': '418116'},
 {'itemId': '329595'},
 {'itemId': '64279'},
 {'itemId': '184370'},
 {'itemId': '157121'},
 {'itemId': '93873'},
 {'itemId': '120050'},
```


Here is a depiction of how historical interactions & real-time interactions data are involved and what those datasets contains: -



- Users Dataset (UserID, User Metadata)
- Items Dataset (ItemID, Item Metadata)
- HISTORICAL Users::Items Timestamped Interaction Dataset (UserID, ItemID, Timestamp)
- LIVE Interactions Event Data (Event Type, Event Value)

The solution system includes an AI processing engine, CRM connection, recommendation engine, and cloud applications, including end to end security and privacy, all integrated to provide the very best product recommendations.

Consumer Data Privacy and Capgemini GDPR Framework: -

These cutting edge Personalization solely rely on Consumers social cues and behavioral patterns. Data governance and privacy policy considerations are given due respect by limiting processing of personal data to what is necessary, protecting data against theft, and granting customers the right to be forgotten. Capgemini own GDPR Framework was in charge of ensuring complete adherence for Customer Data Privacy.

Key Outcomes & Results

Customer value: Personalized recommendations and an interactive experience make shopping more convenient and fun; it's like having a personal stylist or advisor.

Retailer value: Drive more traffic, loyalty, increase basket size and conversions by providing unique and focused customer experiences. An opportunity to collect new insights and utilize them to continually improve the experience. For retailers, it's an opportunity to increase basket size.

Benefit from Amazon huge experience in Retail Recommendations: -

- Recommendations are accurately reflecting business context and user behavior
- Recommendations are responsive to the changing user intent

- Campaign is able to deal with Cold Starts to serve Recommendations to even New Users and even New Items are being recommended
- Solution is backed by cloud native scalable infrastructure and hence it will be able to scale to large collections of users and items

Lessons Learnt

Conclusion

References

1. https://aws.amazon.com/blogs/machine-learning/build-a-movie-recommender-with-factorization-machines-on-amazon-sagemaker/