# A study on developing a hybrid recommender system for Telecommunication Industry in Sri Lanka

Chiran Hewawitharana IM/2016/046

Supervised By: Dr. Chathura Rajapaksha

Co-supervised By: Mr. Dinesh Asanka

SLTMOBITEL
The Connection

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- Progress so far - SLT Project

# Research Problem

# Background of the Research

- The Telecommunication Industry has become the center for digital growth in Sri Lanka.
- 10.9 million (34 per 100 people) internet users and 30.41 million mobile connections (1499 per 1000 people), equivalent to **141.7% of the total population** [Central Bank, 2020]
- SLT Telecom alone is **9 million subscribers** with a growing 91,119 million revenue by 2020. [Sri Lanka Telecom PLC, 2020]
- Recommender Systems are quiet popular and enhancing the business profits in Retail industries. **But no considerable involvement found in Telecommunication Industry in Sri Lankan context.**
- Telecommunication data are highly asynchronous and significantly different compared to retail and other industries.

# Research Problem

- Lack of research for a Recommender System for Telecommunication Industry in Sri Lankan Context.
    - None has addressed recommending fixed-line services.

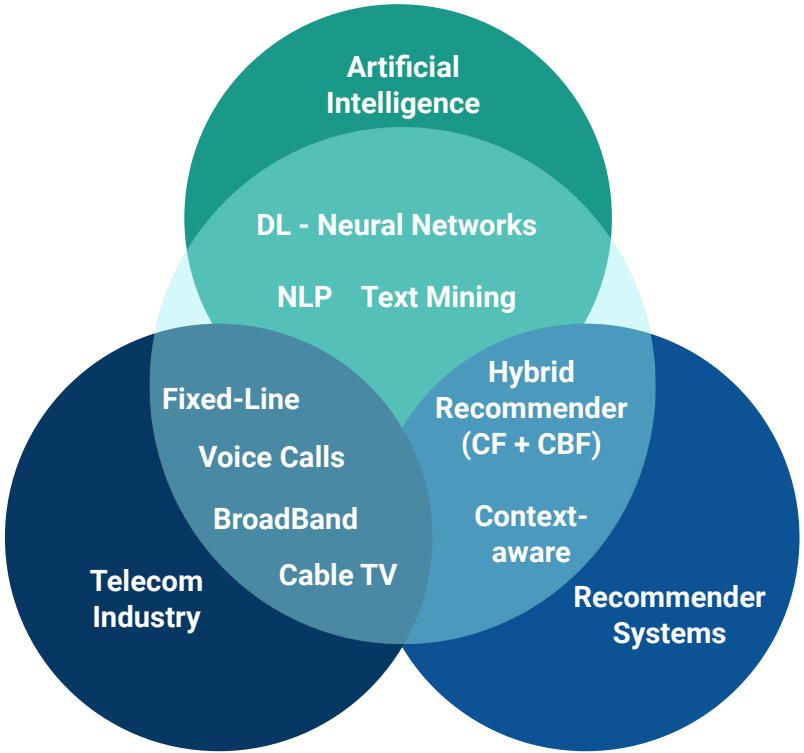
- High availability of Telecom service providers and service packages, subscriber churn has increased.
    - Some services may pass unobserved. If they were recommended when needed, subscriber may continue with the career.
    - Loyal subscribers need to be identified and rewarded with cross-selling and up-selling offers.

# Research Problem

- To address this dynamic market and high competition, a traditional recommender system won't be enough.
  - Issues with Collaborative Filtering approach in a dynamic context (cold-start etc.)
  - User-service interactions, and demographics content alone won't give accurate recommendations.
  - Awareness of Context (Contextual pre-filtering approach) is critical.

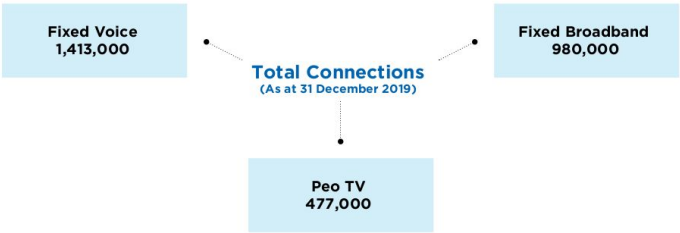
- Recommendation need to be offered to the more beneficial subscriber groups.
  - Subscriber segmentation, identifying and prioritizing target subscriber groups, is crucial for enhancing the business value of recommendations offered.

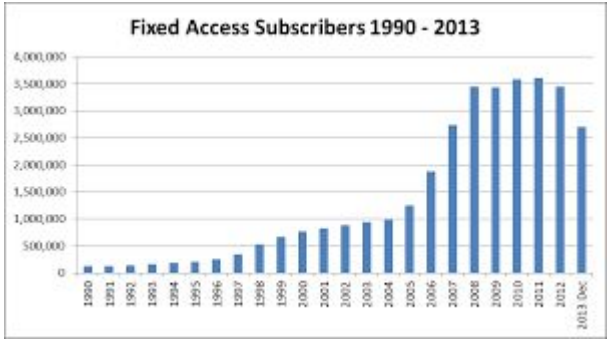
# Research Problem : Scope



# Research Problem : Justification

- Due to high competition, huge variety of services available, Sri Lanka Telecom (SLT) requires a recommender system to recommend services to its beneficial subscribers to increase satisfaction, reduce churn and gain profits.
- There is a dearth of studies done in Sri Lanka in particular telecom sector to implement a recommender system. (Non targeting fixed-line subscribers)
- Acquiring new customers has become multiple times more expensive than retaining a customer. [Chen C., 2016]
- According to [Soft et. al., 2017], as telecommunication services continuously providing different choices to the end user, leading some services to pass unobserved even if useful.

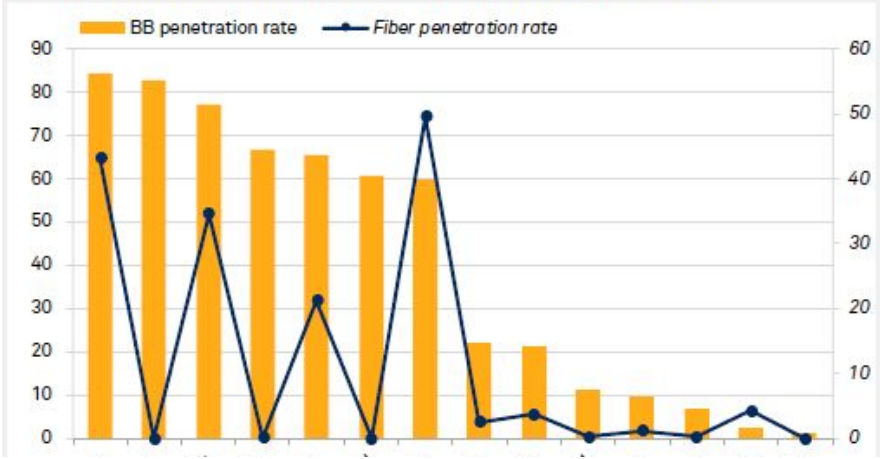


# Research Gap

- There is a dearth of studies done in Sri Lanka in particular telecom sector to implement a recommender system.
- Even though recommender systems are proposed and implemented relevant to the domain, consideration of the context (contextual pre-filtering  approach) is less (or not) considered.
- Requirement of an accurate personalized recommender engine to recommend fixed-line services to subscribers, has arised to meet the company's business strategies.
- This study fills two gaps (practise gap and empirical gap)

# Literature Review



# 01. Recommender System - theories and applications

| Reference | Related findings and suggestions |
| --- | --- |
| [Seyednezhad et. al., 2018] | • Main four methods: Demographic filtering, content-based filtering, collaborative filtering and hybrid methods<br>• CF: Methods of extracting user interactions for a recommendation: Explicit/ Implicit<br>• CBF: make recommendations based on the description of the items. Three parts: content analyzer, profile learner and filtering component.<br>• CBF techniques: Keyword based vector space model<br>• CF techniques: Cosine similarities, KNN - Neighbourhood approach, latent factor model,<br>• Challenges: cold-start problem, multi armed bandit |

# 01. Recommender System - theories and applications

| Reference | Related findings and suggestions |
| --- | --- |
| [Yousef et. al., 2018]<br><br>[Aggarwal CC, 2016] | • Hybrid recommenders: Combination of CF, CBF and Contextual information.<br>• Memory based recommenders: Use of User-item rating matrix, depend on past data.<br>• Model based recommenders: generates a model that learns from the information of user-item ratings and recommends new items.<br>• Hybrid approach: Either CBF-> multi-level CF or CF -> multiclass CBF (user ratings are used as a user feature)<br>• Evaluation methods: Quality of predication validated by MAE (Mean Absolute error), RSME (Root Mean square error) and coverage |

# 02. Recommender Systems in Telecommunication Industry

| Reference | Related findings and suggestions |
| --- | --- |
| [Soft et. al., 2017] | • Importance of recommendation: lose their revenues because of customers switching from one provider to another in search of cheap affordable high-quality products and services.<br>• Lack of a proper understanding of the both current and future(predictive) customer base, and their(predictive) requirements lead to customer churn and revenue lost.<br>• Context features (independent variables) identified: User activity context, time, location, User-item correlation, User satisfaction/opinions (Likert scale values)<br>• having a reduced set of items is more important that having one item recommended. |

# 02. Recommender Systems in Telecommunication Industry

| Reference | Related findings and suggestions |
| --- | --- |
| [Zui Zhang et. al., 2013]<br><br>[Yu,Jian et. al., 2011] | • Suggested approach: to collect new customer information, gather similar existing customer data (purchase records, usage history) and to collect replated product data.<br>• The main characteristics of telcom data is here there could be millions of users and relatively few services.<br>• Unlike enterprise applications which are usually invoked synchronously, telecom applications are always invoked asynchronously.<br>• Proposed algorithms: Generic user/ item based/ item-user/ slope one<br>• ItemAverageRecommender: except that estimated preferences are adjusted for the Users' average preference value.<br>• TreeClustering approach |

# 03. Telecom Big Data Analytics

| Reference | Related findings and suggestions |
| --- | --- |
| [Bursha et. al., 2019]<br><br>[Chen C., 2016] | • With the advancement and of big data technologies, operators are now able to collect more nearly complete data about a user's experience and behavior.<br>• Challenges: capabilities of uncovering insights from large volume of datasets, Velocity and Variety.<br>• Telcom framework contains three horizontal layers – resource, service, and customer, spanning across two vertical perspectives – infrastructure & product and operations.<br>• The telecom data may include, user locations, CRM and call center logs, usage, network performance, subscriber plans, and demography,which may associated with a set of service KPIs (S-KPIs) |

# 04. Context-awareness for recommender systems

| Reference | Related findings and suggestions |
| --- | --- |
| [Adomavicius et. al., 2011] | • Context adds an additional another dimension to the user-item data model of recommender system and can be utilized in different ways during CBF or CF processes.<br>• Representational and interactional context.<br>• Contextual factors to consider: Time context, location purchasing purpose etc.<br>• Knowledge of contextual factors in a recommender system: full or partially observable, unobservable.<br>• Contextual pre-filtering: Context is derived and used prior to the modeling to select the suitable 2D recommender (user x rating)<br>• Exact content can be too wide or narrow. |

# 04. Context-awareness for recommender systems

| Reference | Related findings and suggestions |
| --- | --- |
| [Sundermann et. al., 2019]<br><br>[Bahramian et. al., 2017] | • Context: Physical context, social context, interaction media context and model context.<br>• There are increasing efforts to incorporate the rich information embedded in user's reviews/texts into the recommender systems.<br>• Challenges: difficulty in the acquisition of contextual information. There is a lack of automatic methods for extracting this type of information.<br>• User opinions:  overall opinions, aspect opinions<br>• Interest of a user on an item is usually measured by a rating which can be obtained either<br>• explicitly or implicitly.: Numeric, Ordinal, Binary, Unary |

# 05. Deep Learning Recommender Systems

| Reference | Related findings and suggestions |
| --- | --- |
| [Covington et. al., 2016]<br><br>[Xiangnan et. at., 2017] | • Embedded features to an extended matrix factorization model, which answers the cold-start problem in collaborative filtering, with more precise and accurate recommendations. Introducing **Neural Collaborative Filtering.**<br>• Consideration of data: variety, freshness, and noise<br>• Suggest hybrid recommender model with two deep learning models, extended matrix factorization model (with user context as an additional inputs) for Collaborative filtering called as “candidate generation”.<br>• It returns a shortlisted set of recommendations which then filtered out by Content based recommender model to derive the final set of personalized recommendations. |

# Research Purpose

The purpose of the research is to implement a hybrid-recommender system, which is aware to the user content, interactions and other contextual factors, and able to provide accurate recommendations on fixed-line telecom services offered by the desired company, to its current subscribers.

**Research Approach:** Mixed approach (Qualitative, Quantitative)

# Research Questions

- How do we analyze the relationship between telecommunication subscribers and telecommunication services (packages)?
- What are the challenges telecommunication companies face that lead to high revenue loss, churn and bad customer experience?
- What are the factors affecting in recommending fixed-line telecom services to a subscriber ? (Voice calls, Broadband internet, cableTV)
- What are the identifiable customer segments and how to determine which services/ packages are most applicable/ profitable targeting these segmented groups
- How to provide accurate recommendations considering user interactions and contextual information?

# Research Objectives

- To analyze the relationship between telecommunication subscribers and telecommunication services (packages)
- To identify the challenges telecommunication companies face that lead to high revenue loss, churn and bad customer experience.
- To identify the factors affecting in recommending fixed-line telecom services to a subscriber (Voice calls, Broadband internet, cableTV).
- To identify beneficial subscriber segments and determine which services/ packages are most applicable/ profitable targeting these segmented groups
- To provide accurate recommendations considering user interactions and contextual information.
- To suggest strategies to enhance cross-selling and up-selling of fixed-line telecom services among subscribers through accurate recommendations.

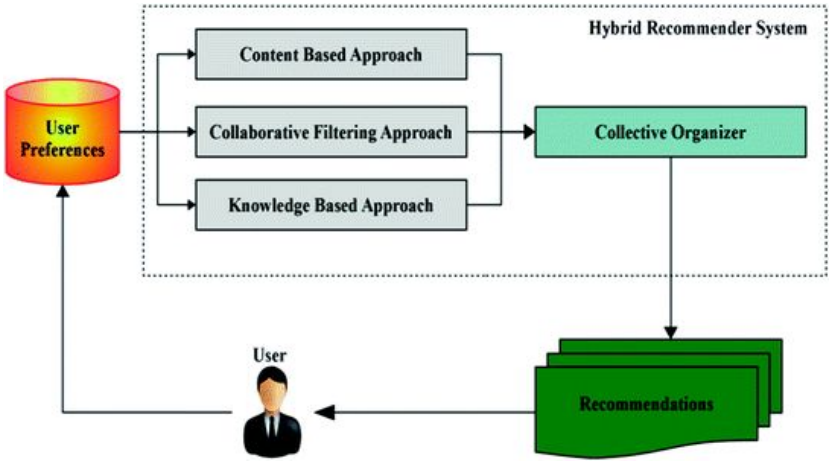
# Proposed Solution

# Proposed Solution

- Developing a **context-aware hybrid recommender system** to recommend telecommunication services (Fixed-line services) to its subscriber segments, targeting cross-selling and up-selling.

- Gathering and extracting contextual features, taken as inputs to the recommender system, in order to provide more accurate recommendations.

- Subscriber segmentation using **uplift-modeling technique** - to identify and prioritize beneficial subscriber groups.



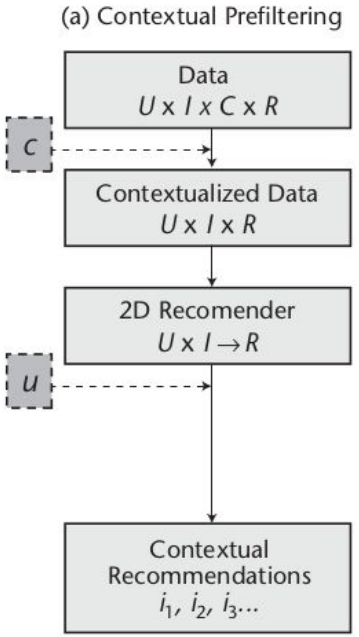
# Proposed Solution

**Why Context is important?**

- Telecommunication services data and user behaviours are dynamic and asynchronous.
- Considering the User-Service interactions, demographic content won't be enough for accurate predictions.

**Contextual pre-filtering:**

- Contextual features, taken as inputs to the model at the time of training.
- Context considered:
  - Business rules
  - Derived user preferences
  - Usage depend on Timeframes/ Locations
  - User reviews and sentiment on services




**U - User data**
**I - Interactions**
**C - Context**
**R - recommendation**

# Proposed Methodology

- A systematic review of literature will be conducted on building a recommender system for telecommunication Industry.

Stage 1

## Data Collection

- **Structured Data**
  * Service Usage: Ratings
  * User demographics
  * conducting a survey
- **Unstructured Data**
  * CRM logs - inquiries/complaints
  * Other user reviews

Stage 2

## Data Analysis and Feature Engineering

- **Developing User Profile**
- **Developing Service/package profiles**
- **Analysis of unstructured text data using text mining, NLP**
- **Extracting contextual information for pre-filtering**

Stage 3

## Development of predictive recommender models

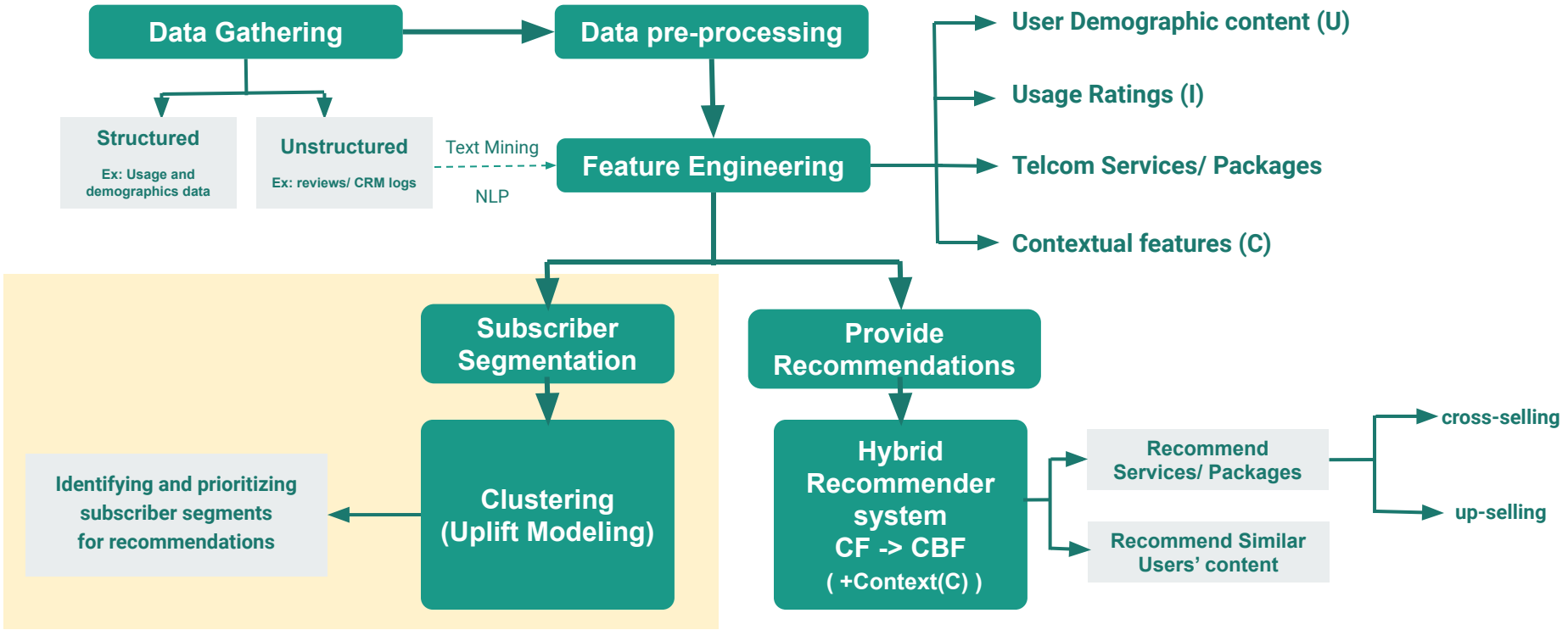
- Comparing available recommender techniques
- Developing deep learning hybrid recommender model(s)

Stage 4

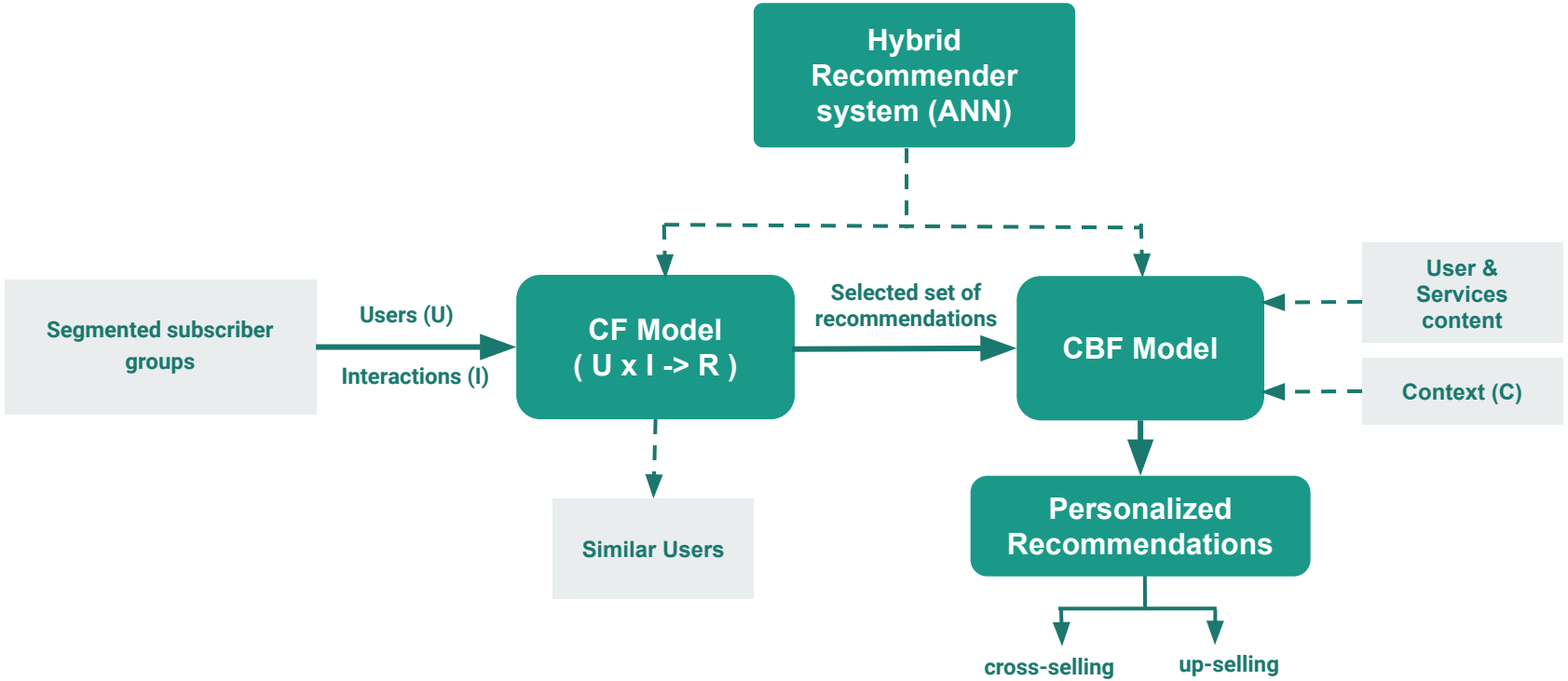
## Testing, Validation and Integration as an end-user service

- Testing and validating the accuracy of predicted results
- Integrating predicted results to a web-based system to be consumed by end-users

# Proposed Methodology cont'd.



# Proposed Methodology cont'd.



# Proposed Solution : Approach

**Solution Approach:**

- Deductive : Aims to prove existing theories within formulated hypothesis
- Predictive: Provide predicted recommendations on past context

**Proposed Technologies:**

- Data pre-processing : Python, Pandas, SQL
- Descriptive analysis: Pandas, numpy, seaborn, matplotlib, plotty
  - Text mining and feature extraction: NLP using Python, NLTK, (Gensim, spaCy)
- Predicting recommendations: Deep-Learning- ANN using Python, Tensorflow, Keras
- Uplift Modeling - Python pylift

# Progress so far : SLT Project

- Descriptive analysis on service usage datasets (VOICE/BB/PEO TV)
- Analysis on ”Product State Changes” dataset
- Building user profile (usage ranks, user location, and interested packages)

To Do:

- Service/ Package profile
- Gather and  extract contextual data : text analysis
- Implementation of feasible recommender models
- Resolve possible problems relevant to recommendation classification
  ( Cold start/ Multi-armed bandit)

# Demonstration

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# Thank You