KYUNG HEE UNIVERSITY

Department of Computer Science & Engineering

Ubiquitous Computing Lab

Extracting User Experience (UX) Dimensions From Qualitative data using UX Qualifiers and Topic Modeling

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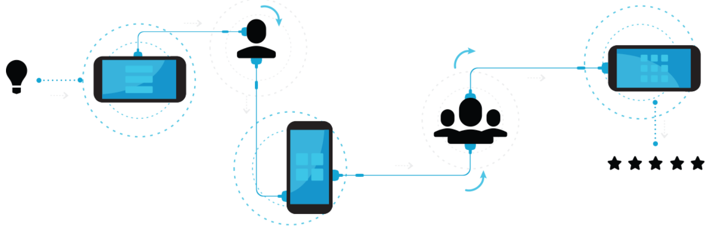

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PRESENTATION AGENDA

INTRODUCTION

- Background
- Motivation
- Problem statement
- Taxonomy
- Related work

PROPOSED SOLUTION

- Solution 1 : UX multi-criteria Qualifiers
- Solution 2 : Topic Extractor

EXPERIMENTS & RESULTS

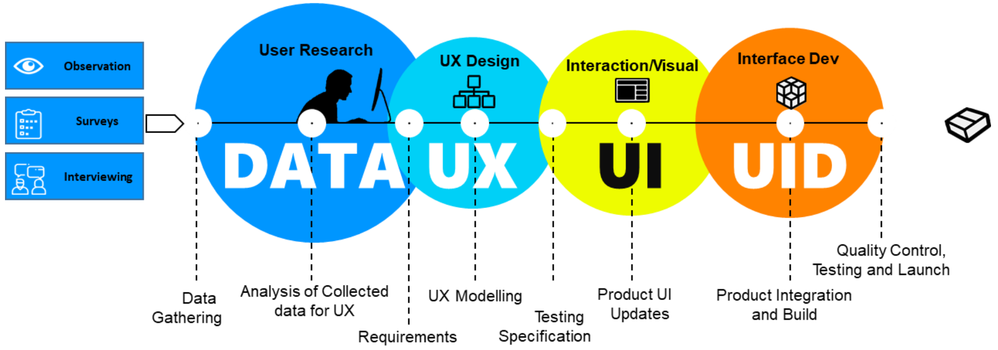
- Dataset
- Experimental setup
- Results & discussion

CONCLUSION

UX Background

UX dimensions Identification

- Customer satisfaction directly affects success of a product, it is vital to understand user experience (UX) in developing a product [1].
- To understand UX , researchers have identified UX dimensions, surveyed quantitative scores on UX dimensions, and conducted a statistical analysis on the collected numbers[2,3,4,5].

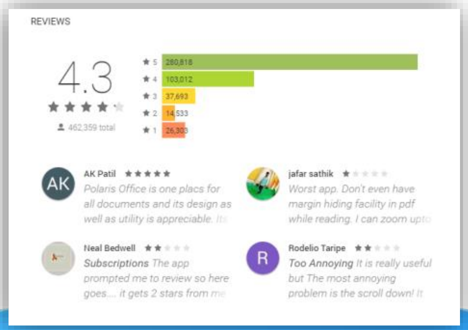


UX | Motivation

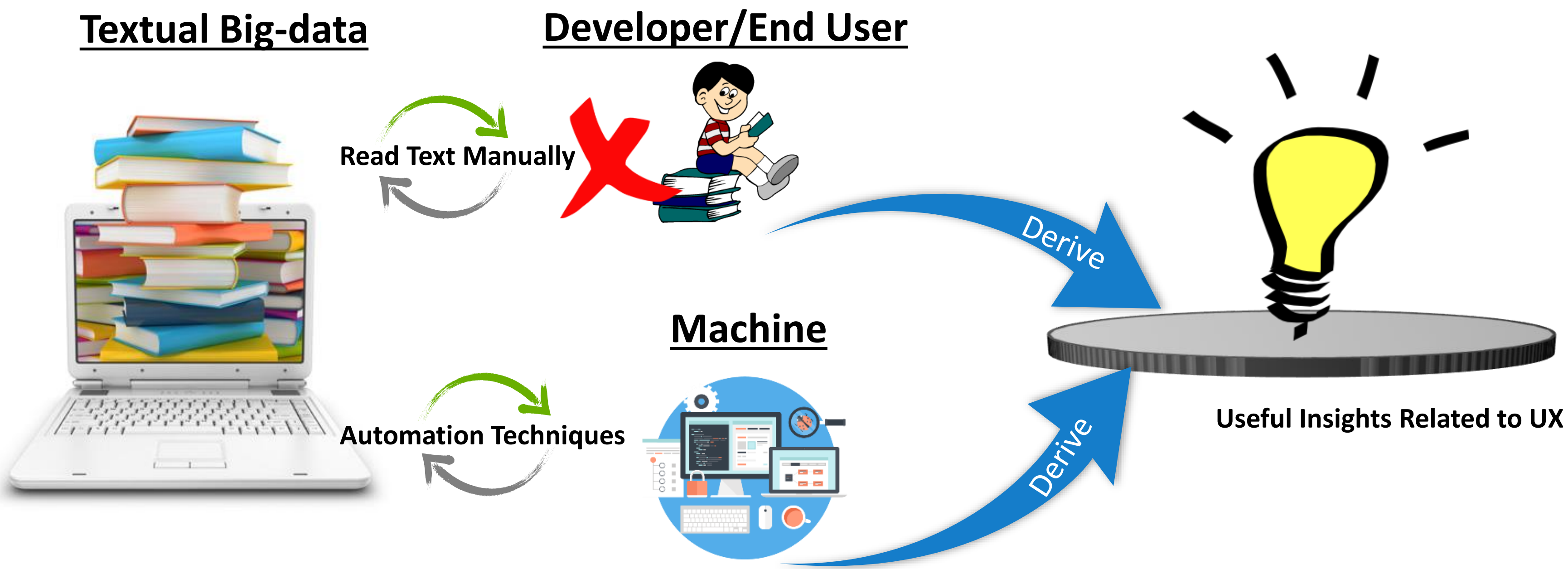
Online User Reviews

Online Reviews benefits

- Contains user opinions (wants and needs etc.)
- Feature requested
- Uses and interacts with the product and service
- Bag reports



Qualitative Data



User Feedback Analysis Process:

- Qualitative data in the form user reviews are available on product distribution platforms
- UX expert examines through reviews manually
- Useful reviews are selected for further analysis
- UX related important construct/dimensions are derived
- These constructs derive product design decisions

The qualitative analysis of these reviews (textual data) is a labor intensive, and prone to researcher bias activity [6].

UX Problem Statement

Problem statement

Probabilistic topic models without **no prior human knowledge** [5] leads to **topics overlapping** , unable to extract the **expected topic** [10], often generate **not interpretable** topics [7].

Goal

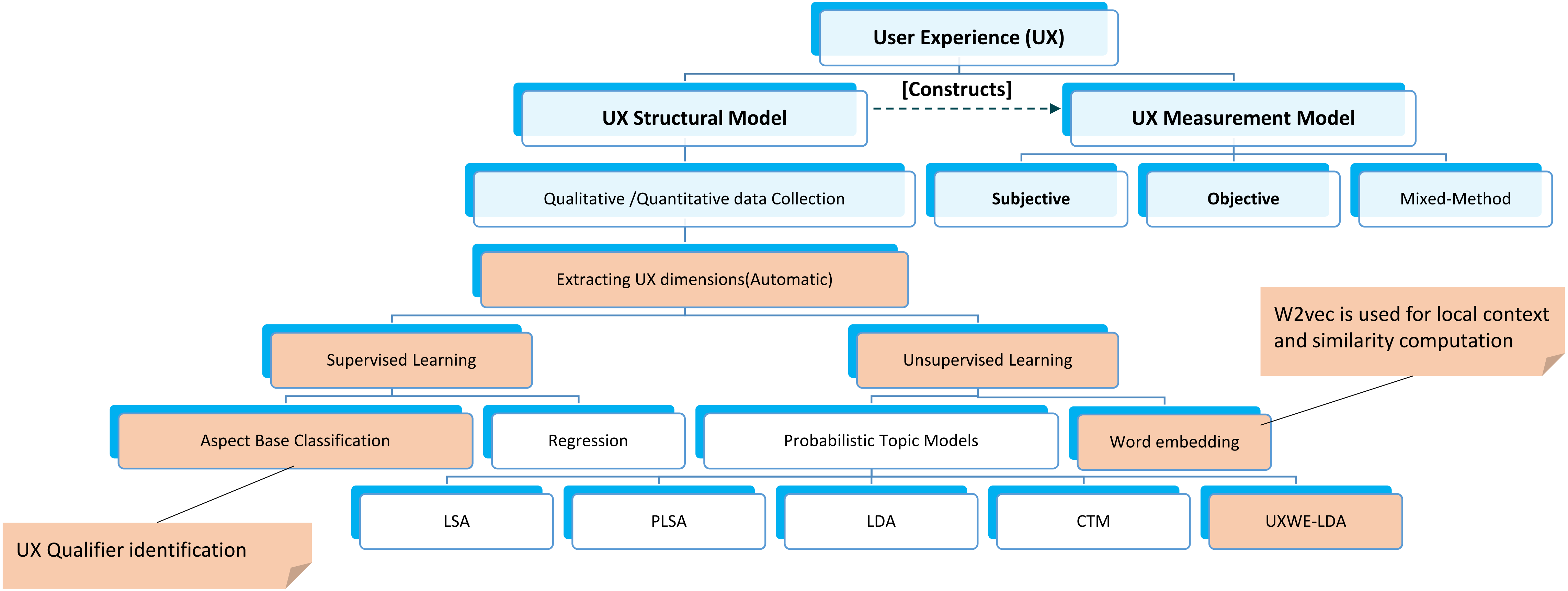
Aims to extract UX dimension from the user reviews along with sentiment orientation for user satisfaction modeling.

Challenges

- **Challenge 1: Usefulness of reviews** [11]
- **Challenge 2: Document heterogeneity** [5]
- **Challenge 3: Similarities computation and Incorporation of domain knowledge** [6][7]
- **Challenge 4: Measuring sentiments toward each UX dimensions on customer satisfaction** [7]

UX Taxonomy

The of taxonomy UX dimension extraction for UX Modeling



UX | Related Work

Review some highlight work in for UX dimension extraction from textual data

	Research	Description	Advantages	Limitation
UX Dimensions Mining	**UX FACETED MODEL:** Exploiting user experience from online customer reviews for product design [8] **(Challenge 1)**	A **faceted conceptual model** is proposed to elucidate the crucial factors of UX from user reviews	**UX knowledge base** from customer online reviews	UX facet extracted from **opinion words**, their algorithm missing most of **product** and **situation features**
	Understanding hidden dimensions in textual reviews [18] **(Challenge 2)**	They modified the **Latent Aspect Rating Analysis (LARA)** for the extraction of hidden UX dimensions in textual reviews	Incorporating both **textual reviews** and **numerical** ratings into assessment	The LARA **need both textual and rating data**. In one cases reviewers **only provide textual emotions in text**.
Topic Modeling (Latent Dimension)	LTM (Lifelong Topic model) [16] **(Challenge 2, 3, 4)**	Learn **knowledge automatically** from multiple domains to improve topics in each domain	Learn the **domain knowledge** automatically	They only use **frequent itemset mining** to mine knowledge from top topical words in multiple domains, do not consider the context
	WE-LDA model [7] **Challenge 2, 3, 4)**	They used word embeddings , which automatically capture both semantic information of words from a large amount of documents	Incorporate word embeddings for the local context	**Sparsity problem** in small dataset

Overall Limitation

- Minimal interest words shadow the semantic relation
- These approaches assume a homogeneity in document collection
- Lack of domain knowledge accommodation for dealing with relative terms problem

UX Limitation, Objective, and Proposed Solution

Limitations and Challenges

Challenge: 1

- Lack of considering the usefulness of reviews before extracting UX dimensions

Challenge: 2,3

- Document heterogeneity
- Similarities computation
- Luck of domain knowledge

Challenge: 4

- Measuring sentiments toward each UX dimensions on customer satisfaction

Proposed Solution

Solution-1

- **UX multi-criteria Qualifiers**
  - Almost unsupervised system based minimal configuration

Solution-2

- **Seed word generation(**Global Context**)**
- **Knowledge Mining (**local context**)**

Solution-3

- **Causal Effect Analyzer**

Objectives

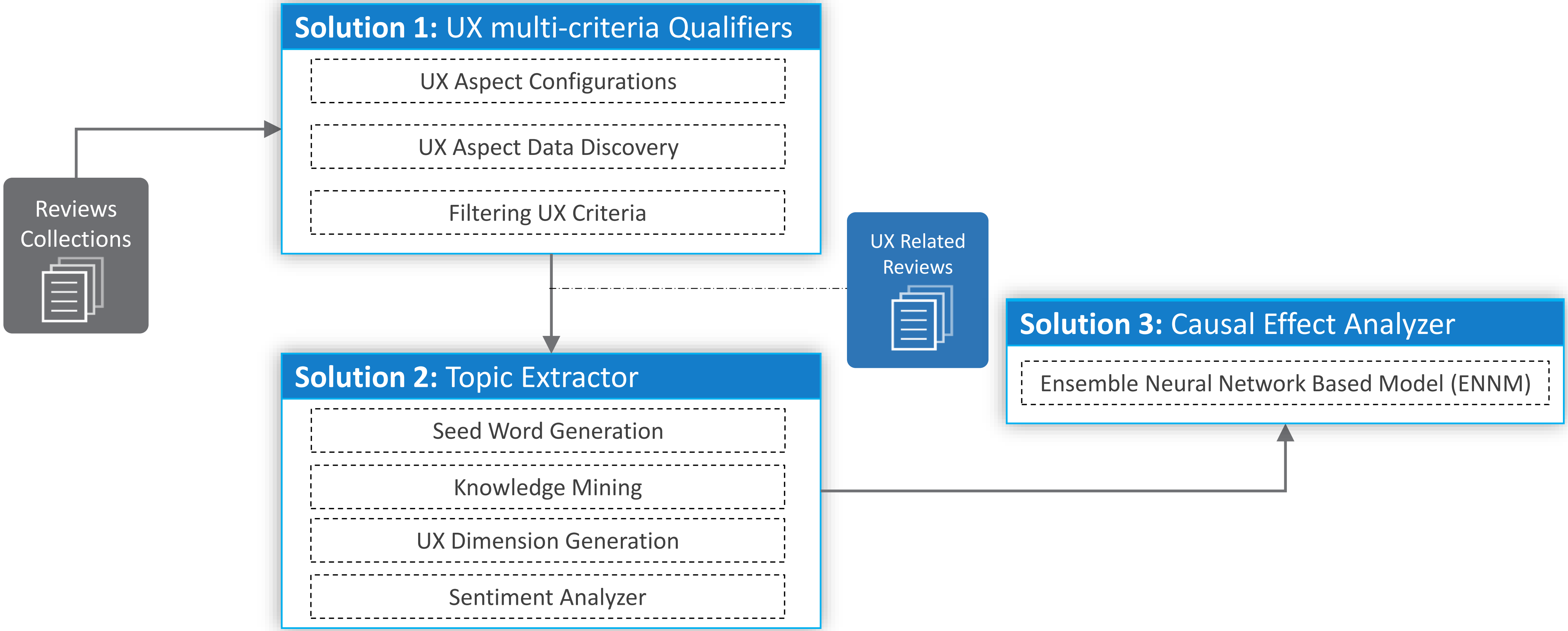
- Find the reviews which contains the information related to UX
- To extract of specific topics of interest for mining the UX dimensions by domain knowledge incorporation
- To measures sentiments toward each UX dimensions on customer satisfaction

Goal

To extract UX dimensions from user reviews (qualitative data) for user satisfaction modeling

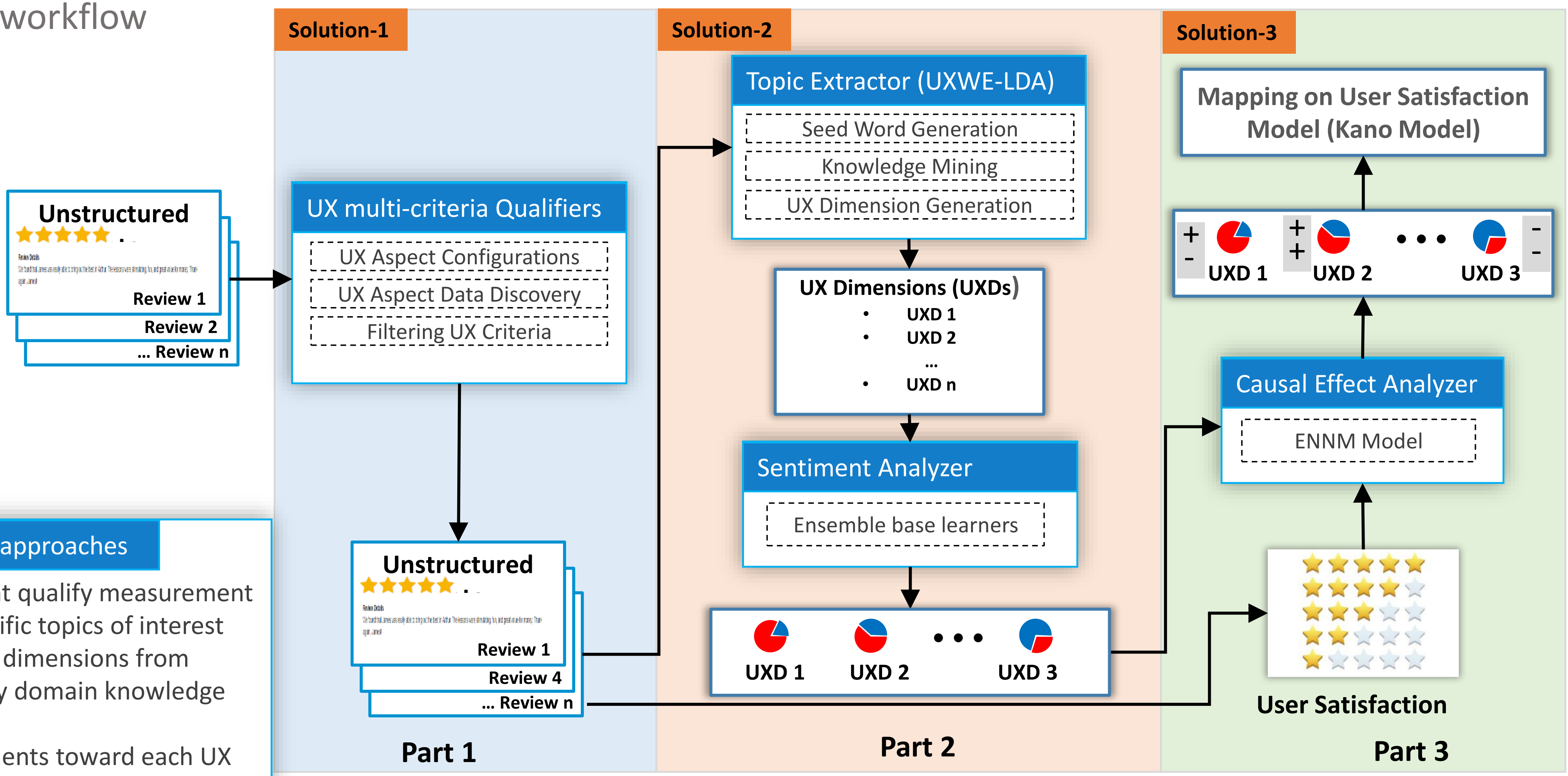
Proposed Methodology

Abstract View



UX Proposed Methodology

Detail workflow

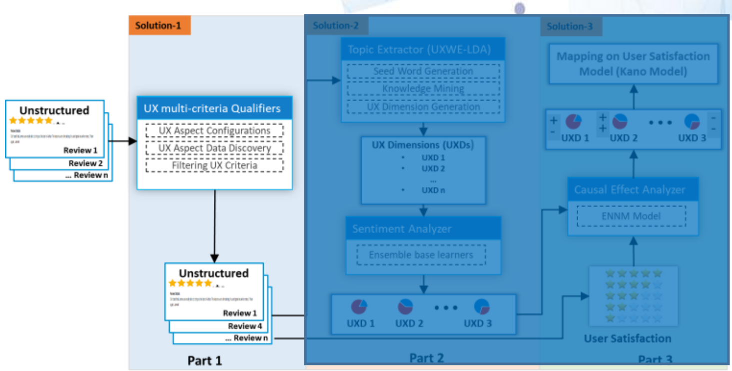


Different to existing approaches

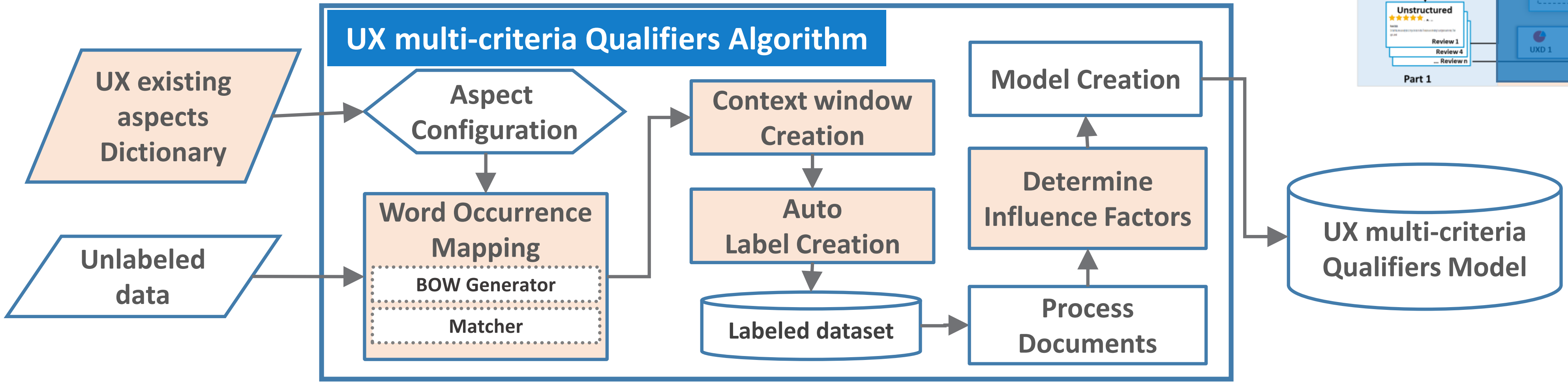
- Reviews document qualify measurement
- Extraction of specific topics of interest for mining the UX dimensions from qualitative data by domain knowledge incorporation
- Measuring sentiments toward each UX dimensions on customer satisfaction.

Solution 1: UX multi-criteria Qualifiers (1/6)

UX multi-criteria Qualifiers(UXMCQ)



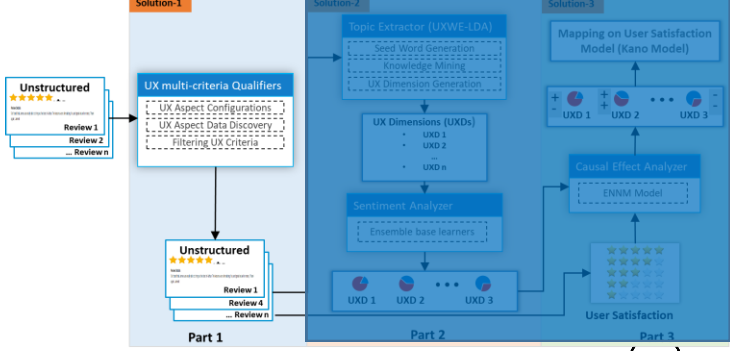
Workflow to obtain the model for UX multi-criteria Qualifiers



- **In UX multi-criteria qualifiers algorithm, we contributes in two components**
  1. **UX existing aspects dictionary creation**, we intend to eliminate the manual selection of terms and ensure the objectivity of the choice of terms, used as gold aspect-terms for UX.
  2. **Word occurrence mapping & context window creation** the occurrences of these words are bootstrapped from the unlabeled domain corpus and modelled according to their two word, corresponding

Different to existing approaches

- Almost unsupervised approach, only requires a minimal domain aspects and sentiment polarity configuration per target domain and language, without requiring additional resources or supervision for UX multi-criteria Qualifiers identification.



Solution 1: UX multi-criteria Qualifiers (2/6)

UX multi-criteria Qualifiers(UXMCQ) → Comparison

Existing Method — UX FACETED MODEL [8]

Challenge: 1

Online User reviews

1 Sentiment Extraction
- Opinion word Extractor
- Sentiment Identification

2 Product Facet Identification
- Frequent Sequence Generation
- Feature Ranking

3 Situation Feature Detection
- Segment Selection
- Learning Process

Sentiment
- A list of opinion words
- The sentiment orientations for review sentences

Product Features
- A list of product features
- The Product Feature in each review sentence

Situation Features
- A list of situation feature
- The situation feature in each review sentences

Proposed Idea

1 Domain Aspect Configuration
- Product Aspects
- User aspects (Sentiment)
- Product Aspects

2 User reviews

3 UX multi-criteria Qualifiers
- Aspects Identification

4 Modelled Aspects
- Product Aspects
  - Aspects Terms
- User Aspects
  - Positive words
  - Negative words
- Situation Aspects
  - Aspects Terms

5 Online User reviews

6

Sentiment
- A list of opinion words
- The sentiment orientations for review sentences

Product Features
- A list of product features
- The Product Feature in each review sentence

Situation Features
- A list of situation feature
- The situation feature in each review sentences

Existing Approach Limitations

- ❑ Opinion words, they missing most of product and situation features

Solution for challenge 1

- ❑ Mostly unsupervised approach with Domain Aspect Configuration

UX Solution 1: UX multi-criteria Qualifiers (3/6)

UX multi-criteria Qualifiers(UXMCQ) → **Comparison – Algorithm wise**

Existing Method

UX FACETED MODEL [8]

Challenge: 1

Algorithm 1: UX data discovery

Input: Candidate feature set F. Opinion word set Y

Output: Product feature set f

1. **for** each s in F **do**
2. Calculate term frequency in reviews: $tf(s)$
3. Calculate the number of opinion sentences containing no s: $n(\bar{s}, Y)$
4. Calculate the number of non-opinion sentences containing s at least once: $n(s, \bar{Y})$
5. Calculate the distance between s and the opinion word at sentence level: $d(s, Y)$
6. Calculate the term weighting of s:
   $$w_s = tf(s) \cdot \log\left(1 + \frac{d(s,Y)}{n(\bar{s},Y)+1} \frac{d(s,Y)}{n(s,\bar{Y})+1}\right)$$
7. **end for**
8. Sort items in F based on their term weightings
9. Save the top k of F in product feature set f

Existing Approach Limitations

- ❑ Opinion words, they missing most of product and situation features

Proposed Idea

Algorithm 1: UX multi-criteria Qualifiers(UXMCQ)

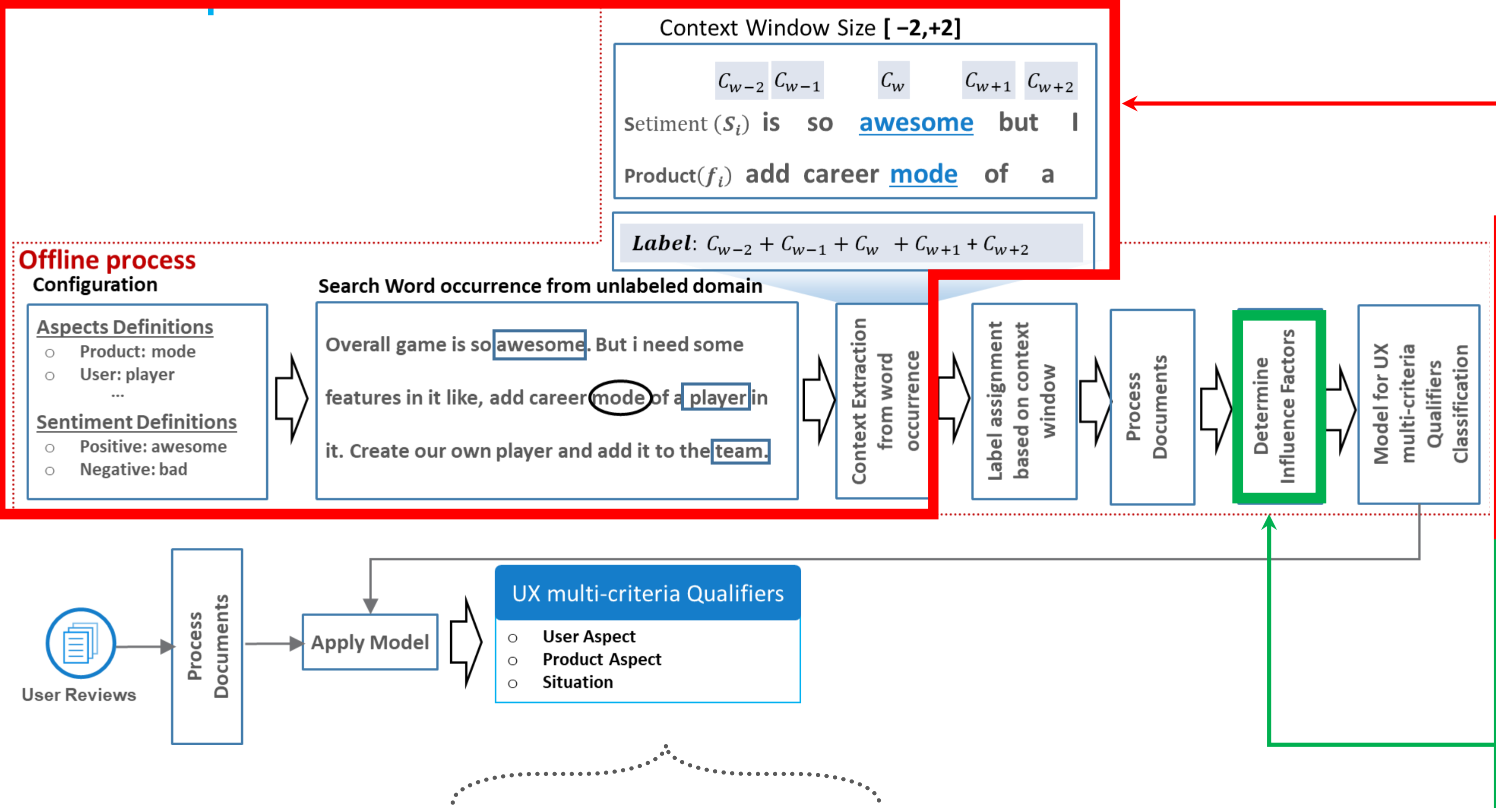
Input : $A_d = \{D_1, D_2, D_3, .., D_i, ..., D_n\}$ // Aspects definition
$B_W = \{w_1, w_2, w_3, .., w_i, ..., w_n\}$ // Bag of words of size n
$F_s = \{f_1, f_2, f_3, .., f_j ..., C_n\}$
λ = Threshold value

Result: UX multi-criteria Qualifiers(UXMCQ) Model

Initialization ;
$C_{size} \leftarrow [+n, -n]$;
$Y_i \leftarrow 0$;
$f \leftarrow newSet()$;
foreach D_i *in* A_d **do**
  if *matched* D_i *in* B_W *do* **then**
    $C_W \leftarrow createContextWindow(B_W, D_i, C_{size})$;
    $Y_i \leftarrow toLabeledData(C_w)$
  end
end
foreach f *in* F **do**
  $X_F \leftarrow rankFeatures(y_i, F)$
  $X_F \leftarrow sortDES()$
  $T_F \leftarrow selectTopKFeatures(X_F, k)$
  $R_F.add(T)$
end
$R_F \leftarrow majorityVoting(R_F, >t)$;
$UXMCQModel \leftarrow trainModel(R_F, classifier)$;

UX Solution 1: UX multi-criteria Qualifiers (4/6)

UX multi-criteria Qualifiers(UXMCQ)



$$Ux_q = \begin{cases} hepfulness(r_i) + QualifierNum(r_i) \geq 1 & \textbf{Hepfulness}(r_i) \textbf{ and } \textbf{QualifierNum}(r_i) \\ 0, & Otherwise \end{cases}$$

Algorithm 1: UX multi-criteria Qualifiers(UXMCQ)

Input : $A_d = \{D_1, D_2, D_3, .., D_i, ..., D_n\}$ // Aspects definition
$B_W = \{w_1, w_2, w_3, .., w_i, ..., w_n\}$ // Bag of words of size n
$F_s = \{f_1, f_2, f_3, .., f_j ..., C_n\}$
λ = Threshold value

Result: UX multi-criteria Qualifiers(UXMCQ) Model

Initialization :
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- **foreach** D_i *in* A_d **do**
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    - $Y_i \leftarrow toLabeledData(C_w)$
  - **end**
- **end**
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  - $X_F \leftarrow sortDES()$
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- **end**
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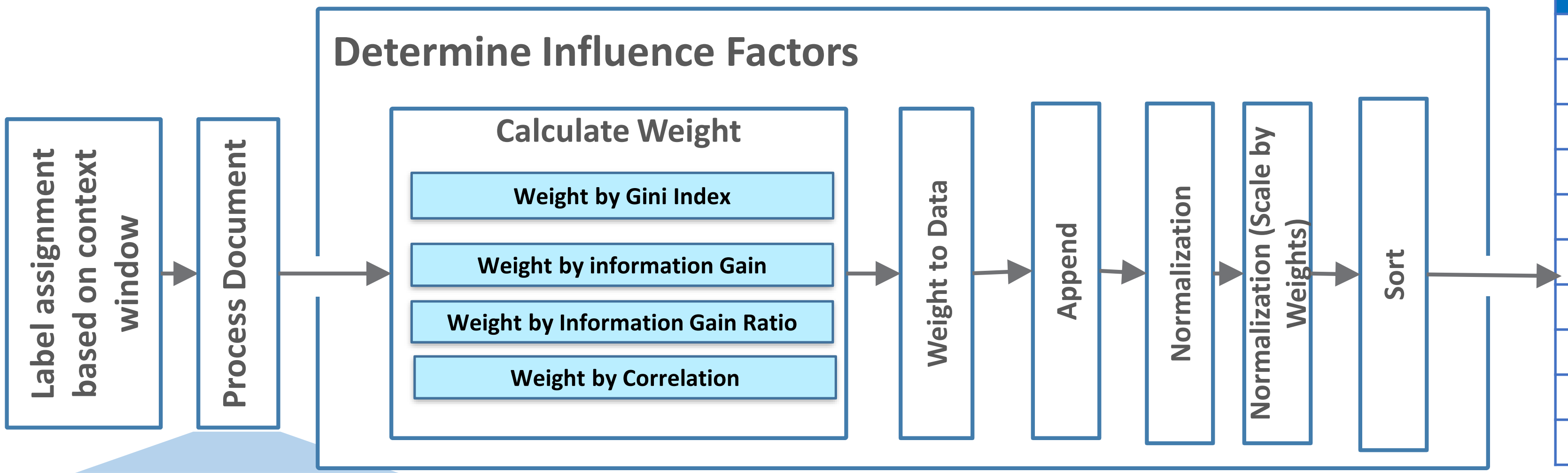
Related Publication

- Hussain, Jamil, et al. "A multimodal deep log-based user experience (UX) platform for UX evaluation." *Sensors* 18.5 (2018): 1622.
- Hussain, Jamil, and Sungyoung Lee. "Mining user experience dimensions from mental illness apps." International Conference on Smart Homes and Health Telematics. Springer, Cham, 2017.
- Hussain, Jamil, and Sungyoung Lee. "Identifying user experience (UX) dimensions from UX literature reviews."

Solution 1: UX multi-criteria Qualifiers (5/6)

Usefulness of reviews - **Determine Influence Factors** - **Example**



Attribute	Weight
good	1.0
friendly	0.944476693026509
staff	0.9007143962349031
room	0.8981129039166721
location	0.7489147043866663
nice	0.6749096492620802
noisy	0.5492830202802824
great	0.539918796116805
excellent	0.5240543237068682
window	0.499768075746836

- Language Detection
- Spell correction
- Tokenization
- Stop words Removal
- Stemming
- POS_Tag (N/JJ/V)

Language Detection

- User Write reviews in different languages

Spell correction

- Most of user writes reviews in informal language: used short words(gr8) , and have many incorrect spelling

Tokenization

Filter Stop Words

- prepositions, pronouns and conjunctions

Stemming

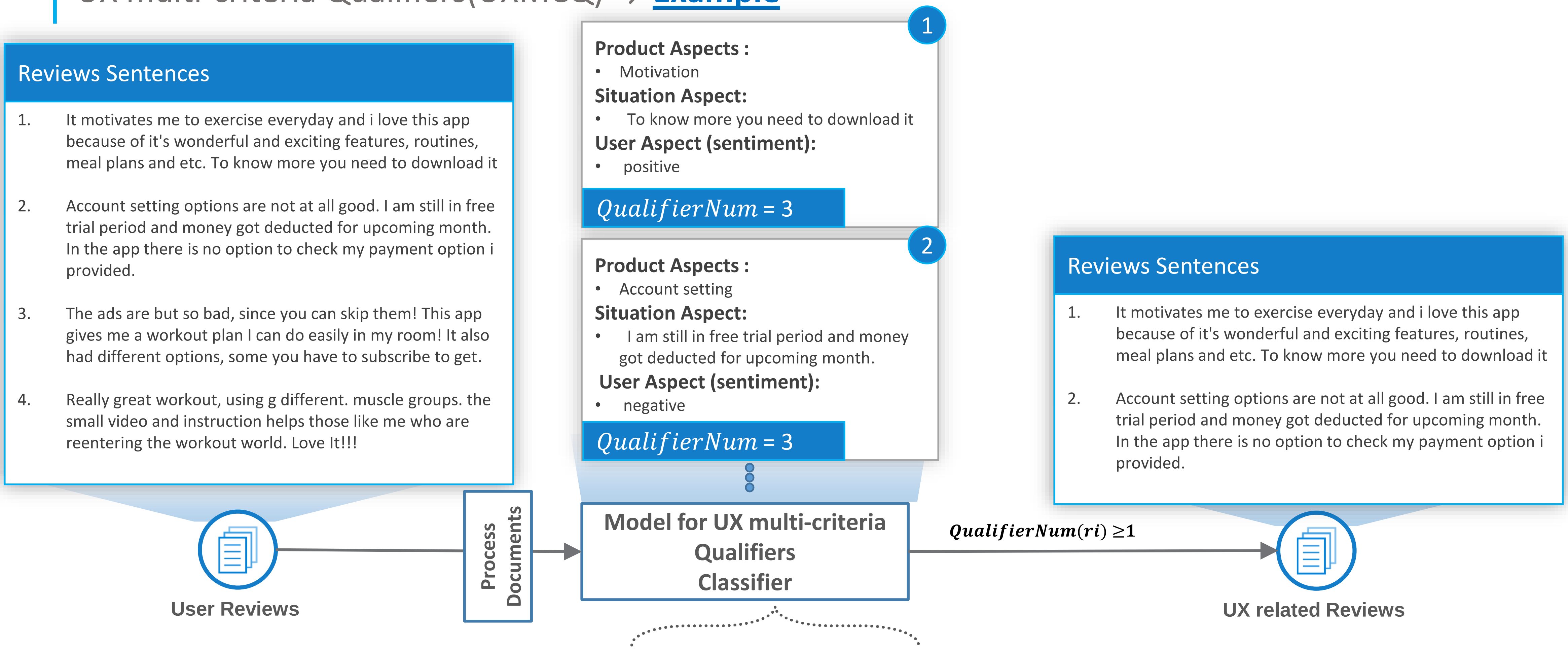
- Porter stemming algorithm
  - ✓ $[C](VC)^m[V]$

POS-Tag

- Filter only noun, adjective and verbs using Peen tree algorithm
  - ✓ Regx - **(N/JJ/V)**

UX Solution 1: UX multi-criteria Qualifiers (6/6)

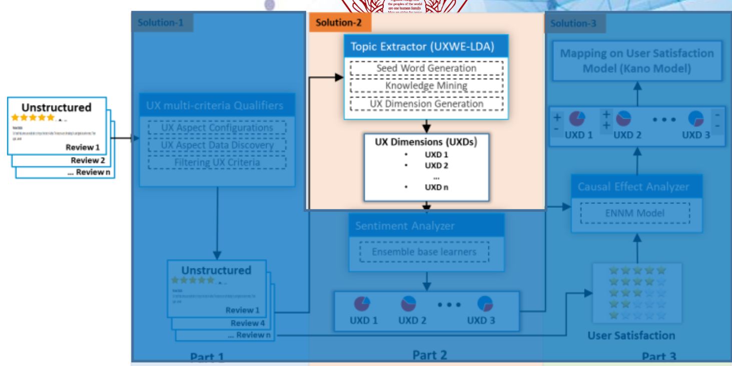
UX multi-criteria Qualifiers(UXMCQ) → **Example**



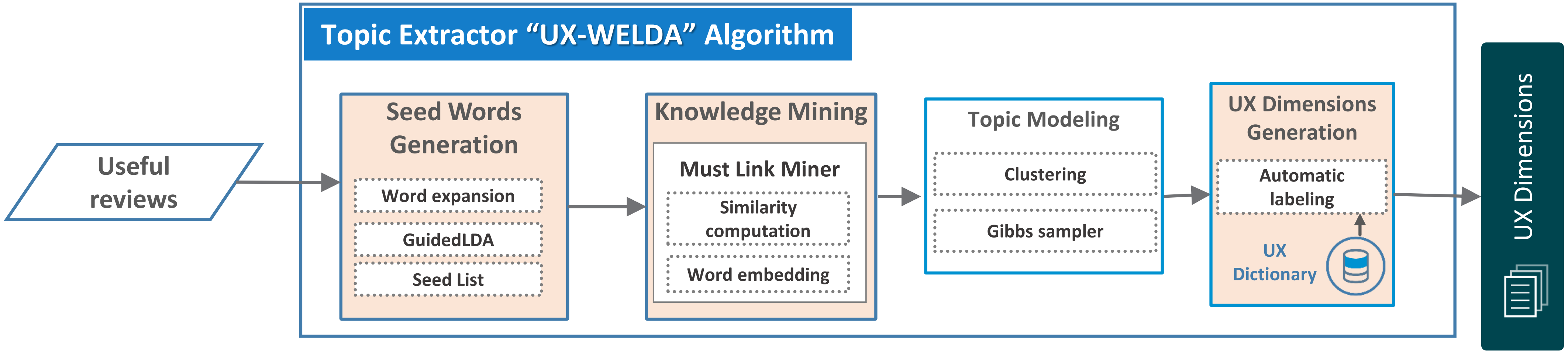
$$Ux_q = \begin{cases} hepfulness(r_i) + QualifierNum(r_i) \geq 1 & \textbf{Hepfulness}(r_i)\ \textbf{and}\ \textbf{QualifierNum}(r_i) \geq 1, \\ 0, & Otherwise \end{cases}$$

UX Solution 2: Topic Extractor

Topic Extractor → **Incorporation of domain knowledge**



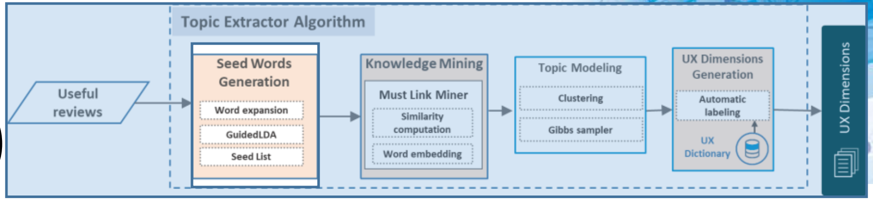
Workflow for Topic Extractor Algorithm



- **In topic extractor algorithm, we contributes in three components**
  1. **Seed Words generation**, global context generation
  2. **Knowledge Mining,** automatically capture both semantic and syntactic information, which improves the semantic coherence significantly in topic extraction
  3. **Automatic labeling** of extracted topics based on the UX dictionary.

Different to existing approaches

- Automatically learn the domain knowledge from global and local context.



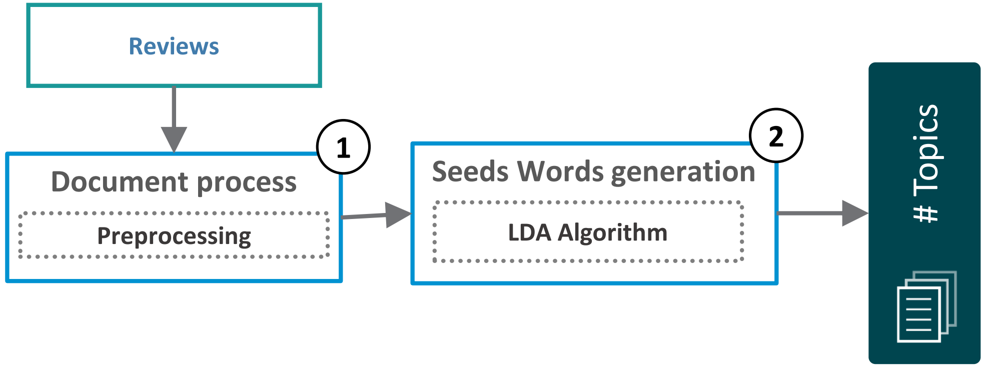
Solution 2-1: Seed words generation(1/4)

Seed words generation → **Comparison**

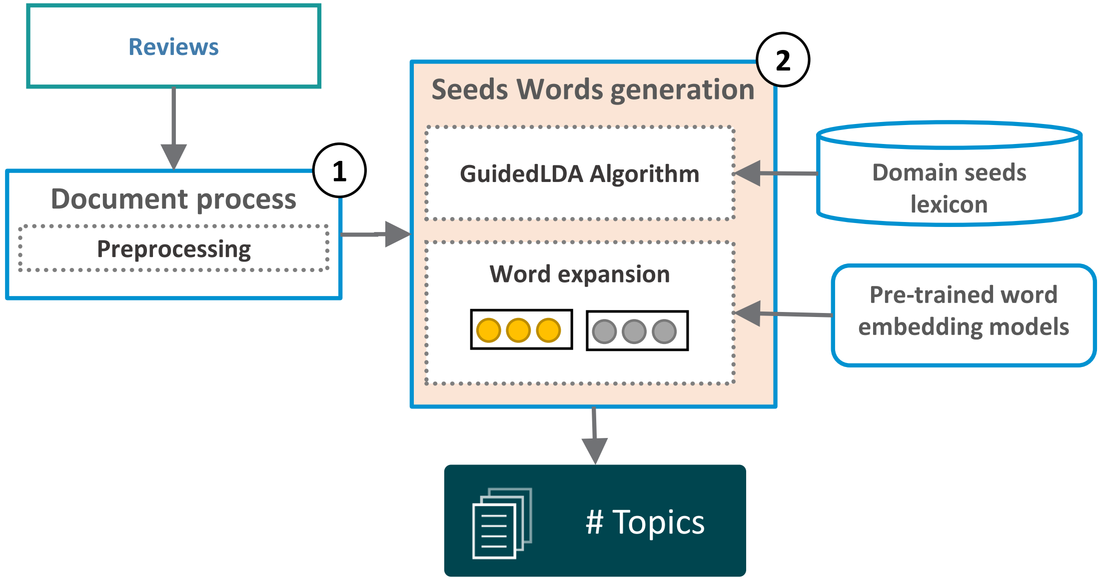
Existing Method

WE-LDA model [7,16,18]

Challenge: 2



Proposed Idea

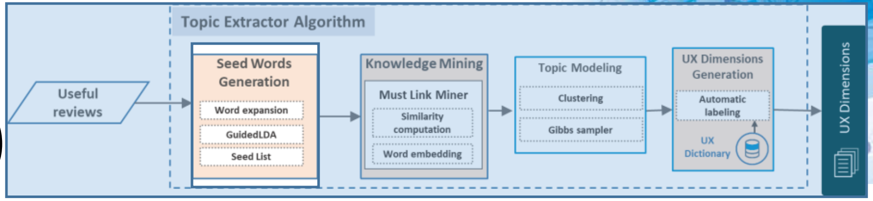


Existing Approach Limitations

- ❑ They don’t considered the syntactic and semantic relationships

Solution for challenge 2

- ❑ Pre-trained word embedding space for syntactic and semantic relationships



UX | Solution 2-1: Seed words generation(2/4)

Seed words generation → Comparison - Algorithm wise

Proposed Idea

Existing Method

WE-LDA model [7,16,18]

Challenge: 2

Algorithm 2 : Seed words generation algorithm

Input: training data X, the number of topics K, hyperparameters α, β
Output: topic assignment matrix Z, topic-document matrix M, word-topic matrix N

Initialize M, N to zeros
for document $j \in [1, D]$ **do**
  for token position i in document j **do**
    $Z_{ij} = k \sim Mult(\frac{1}{K})$
    $M_{kj} += 1; N_{wk} += 1$
  end for
end for
repeat
  for document $j \in [1, D]$ **do**
    for token position i in document j **do**
      $M_{kj} -= 1; N_{wk} -= 1$
      $Z_{ij} = k' \sim p(Z_{ij} = k | rest)$
      $M_{k'j} += 1; N_{wk'} += 1$
    end for
  end for
until convergence

Algorithm 2 : Seed words generation algorithm

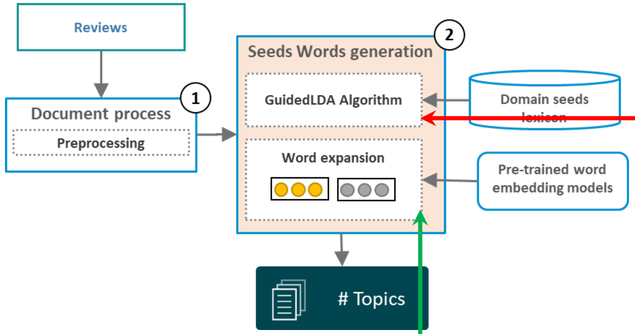
Input : Useful reviews corpus C,
Seed topic words S_d
External corpur C
Vector dimension k
Vector dimension k
Result: The global context for user reviews text W_t

foreach *(doucment $d \in C$)* **do**
  Sampling a topic form a topic's multiple distribution.
  $Z_d \sim Mul(\theta)$
  foreach *word* $\in$ *document d where* $W \in (wd_1, wd_2, ...wd_n)$ **do**
    Generate a variable weight probability from the Bernulli distribution the prbability of under t estimated by guided LDA
    $W_t = n - argmar_w \varnothing(w, s_d)$
  end
end
$W2VTrain(C, k)$
$VocabSize \leftarrow getVocabSize(C)$
$V \leftarrow initVector(vocabSize, k)$
$\theta \leftarrow initVector(vocabSize, k)$
for $(W_i \in C)$ **do**
  $e \leftarrow 0$
  $Xw \leftarrow \Sigma u \in context(W_i)V(u)$
  for $(u = w_i UNEG(w_i))$ **do**
    $e \leftarrow e + g\theta^u$
  end
  for $(u \in Context(w_i))$ **do**
    $V(u) \leftarrow -V(u) + e$
  end
end
$t' = V(W_t, k)$
$expenedWord \leftarrow 0$
for $(t' \in W_t)$ **do**
  $\delta(t, t') = \frac{\sum_i^l u_i.v_i}{\sqrt{\sum_i^l u_i^2}.\sqrt{\sum_i^l v_i^2}}$
  if $(\delta(t, t') > \alpha)$ **then**
    $expendedWord \leftarrow t'$
  end
end
$W_t = W_t + expendedWord$
return W_t

UX Solution 2-1: Seed words generation(3/4)

Seed words generation → Global context

- The Guide LDA gives us global context based on seed list
- The pre-trained word embedding model for word expansion



Guided LDA

$$W_t = n - argmar_w \, \varnothing \, (w, s_d)$$

Word Expansion

$$W_{t,t'} = \begin{cases} \boldsymbol{w}(t,t') & if\, \boldsymbol{w}(t,t') > \alpha \\ 0 & Other\ wise \end{cases}$$

$$\boldsymbol{w}(t,t') = \frac{\sum_i^l u_i . v_i}{\sqrt{\sum_i^l u_i^2} . \sqrt{\sum_i^l v_i^2}}$$

Contributions

- A novel data representation for topic modeling based on syntactic and semantic relationships derived from distances calculated within a pre-trained word embedding space

Algorithm 2 : Seed words generation algorithm

```
Input  : Useful reviews corpus C,
         Seed topic words S_d
         External corpur C
         Vector dimension k
         Vector dimension k
Result: The global context for user reviews text W_t
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    Sampling a topic form a topic's multiple distribution.
    Z_d ~ Mul(θ)
    foreach word ∈ document d where W ∈ (wd_1, wd_2, ...wd_n) do
        Generate a variable weight probability from the Bernulli distribution the prbability
        W_t = n − argmar_w ∅(w, s_d)
    end
end
W2VTrain(C, k)
VocabSize ← getVocabSize(C)
V ← initVector(vocabSize, k)
θ ← initVector(vocabSize, k)
for (W_i ∈ C) do
    e ← 0
    Xw ← Σu ∈ context(W_i)V(u)
    for (u = w_i UNEG(w_i)) do
        e ← e + gθ^u
    end
    for (u ∈ Context(w_i)) do
        V(u) ← −V(u) + e
    end
end
t' = V(W_t, k)
expenedWord ← 0
for (t' ∈ W_t) do
    δ(t, t') = Σ_i^l u_i.v_i / (sqrt(Σ_i^l u_i^2) · sqrt(Σ_i^l v_i^2))
    if (δ(t, t') > α) then
        expendedWord ← t'
    end
end
W_t = W_t + expendedWord
return W_t
```
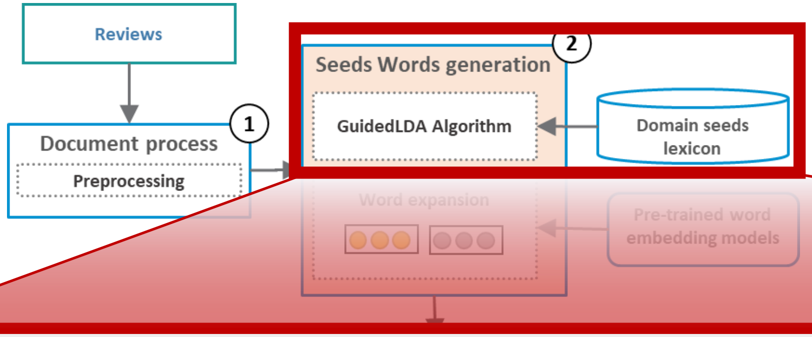

Related Publication

- Hussain, Jamil, and Sungyoung Lee. "Mining user experience dimensions from mental illness apps." International Conference on Smart Homes and Health Telematics. Springer, Cham, 2017.
- Hussain, Jamil, et al. "A multimodal deep log-based user experience (UX) platform for UX evaluation." *Sensors* 18.5 (2018): 1622.

UX | Solution 2-1: Seed words generation(3/4)

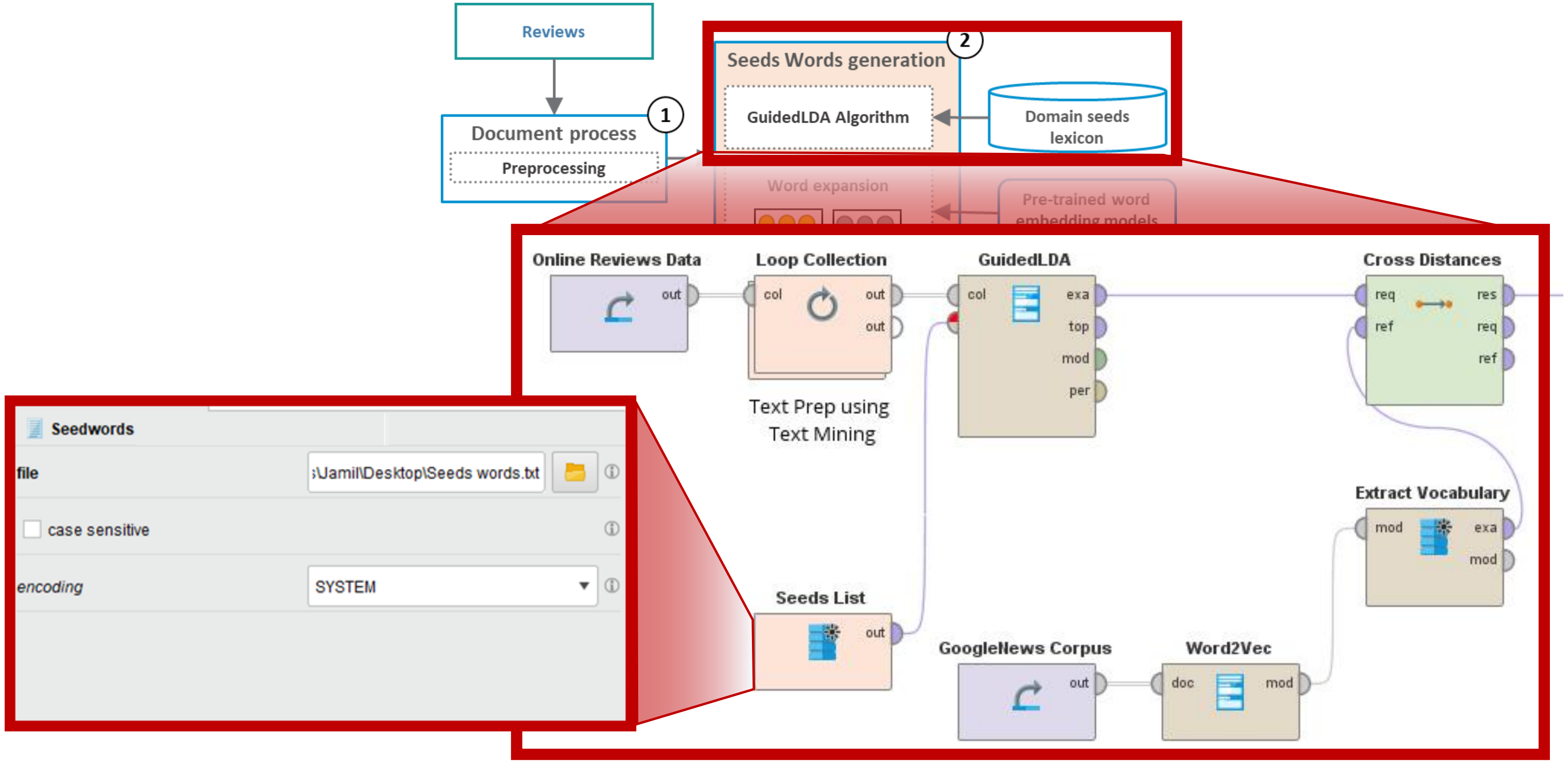
Seed words generation → **Global context**




```
seed_topic_list = [['game', 'team', 'win', 'player', 'season', 'second',
'victory'],['percent', 'company', 'market', 'price', 'sell',
'business', 'stock', 'share'] … ]

model = guidedlda.GuidedLDA(n_topics=5, n_iter=100, random_state=7, refresh=20)
```

Solution 2-1: Seed words generation(3/4)

Seed words generation → **Global context**



Solution 2-1: Seed words generation(4/4)

Seed words generation – Global context → **word expansion : Example**

	Centroid: chat
Semantically similar words	chatroom, conversation , conversing, talk, conversed, Live_Chat, message, interview, speak,
Syntactically similar words	Chats , chatting , Chat, chatted

t: Chat

Pre-train word embedding model

t': #top similar words
chatroom
conversation
conversing
talk
blogging
Live_Chat
message
speak
Chats
chatting
Chat
chatted

Compute Similarity

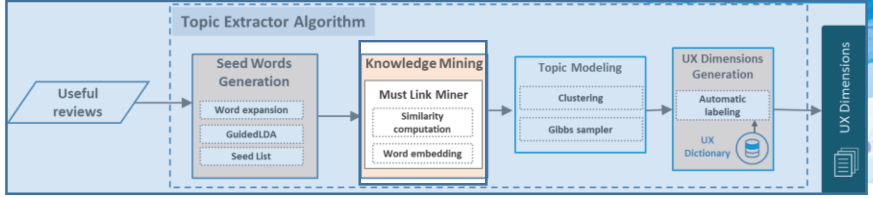
t': #most similar words
chatroom
conversation
conversing
talk
Live_Chat
message
speak
Chats
chatting
Chat
chatted

Semantically similar words	Syntactically similar words
chatroom	Chats
conversation	chatting
conversing	Chat
talk	chatted
Live_Chat	
message	
speak	

We use stemming algorithm and compare the stem word with of both t and t'. If both stem word equal then it is Syntactically similar words

UX

Solution 2-2: Knowledge Mining (1/4)

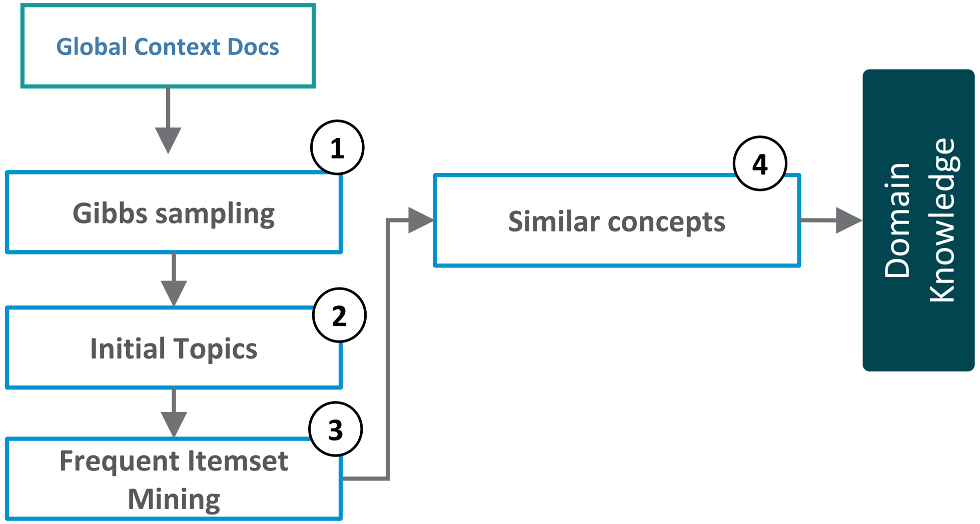


Knowledge Mining → **Comparison**

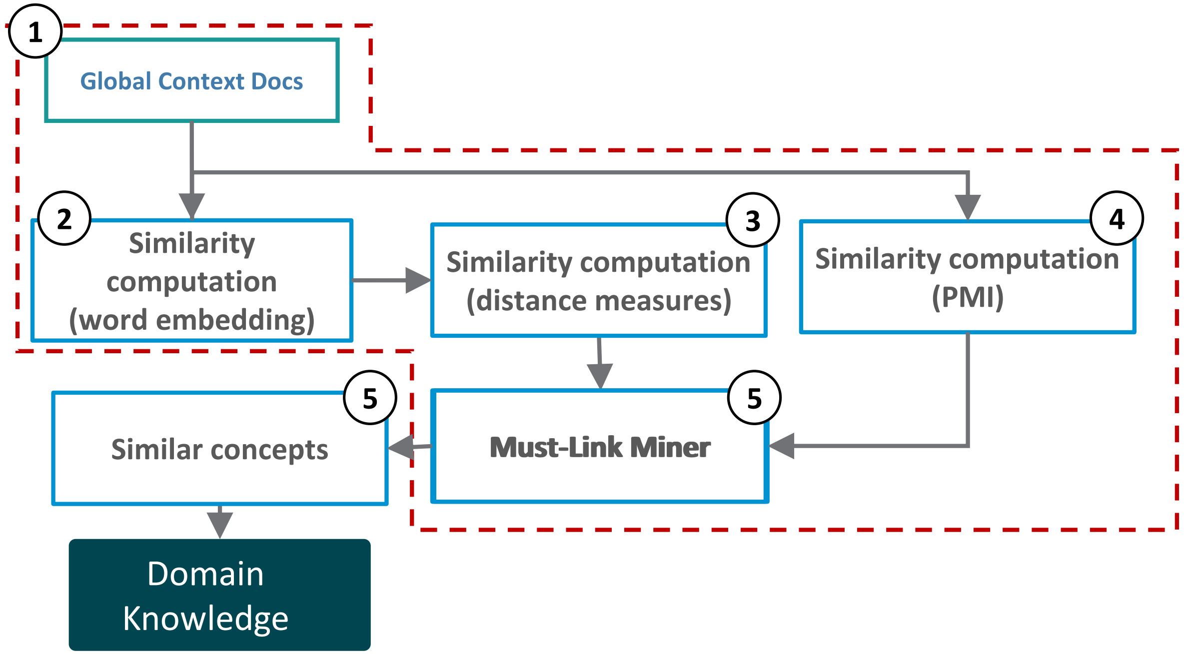
Existing Method

Knowledge Mining [7, 21]

Challenge: 2 and 3



Proposed Idea



Existing Approach Limitations

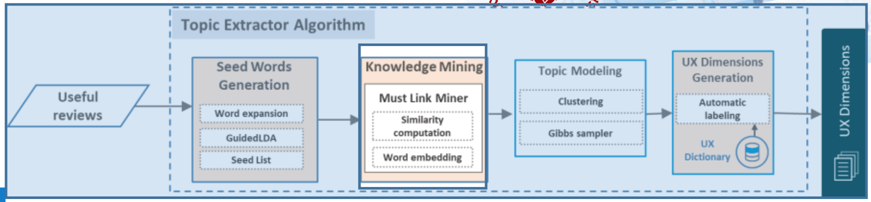
- ❑ Frequent itemset mining
- ❑ Order of words in text

Solution for challenge 2

- ❑ Musk-link mining -> Incorporate word embedding and other similarity computation

Solution 2-2: Knowledge Mining (2/4)

Knowledge Mining → **Comparison**



Existing Method

Knowledge Mining [7, 21]

Challenge: 2 and 3

Algorithm 3 : Knowledge Mining

Input: Word distribution under topics φ_t from LDA
LR-sets $\{1, \dots, S\}$
Output: C

```
For each LR-set s ∈ {1,...,S}
    For each pair (w, w') ∈ s
        P_max(w) = max_{t∈{1...T}} φ_t(w);
        P_max(w') = max_{t∈{1...T}} φ_t(w');
        If P_max(w) > P_max(w') then
            Exchange w and w';
        t_max = argmax_{t∈{1...T}} φ_t(w');
        C_{s,w',w} = φ_{tmax}(w) / φ_{tmax}(w');
Return C;
```

Existing Approach Limitations

- ❑ Frequent itemset mining
- ❑ Order of words in text

Proposed Idea

Algorithm 3 : Word embedding vector generation algorithm

Input : Global Context Corpus $C_d = \{d_1, d_2, d_3, \dots, d_n\}$,
Context Window c
Result: Word Embedding Vector V

```
Word embedding Vector V⃗
foreach (document D ∈ C_d) do
    foreach (word w ∈ D) do
        Compute P(W_{x+c}|W_x) = exp(vwx.vwx) / Σ_{w=1}^{V} exp(vw.vwx)
        V⃗ ← P(W_{x+c}|W_x)
    end
end
return V⃗
```

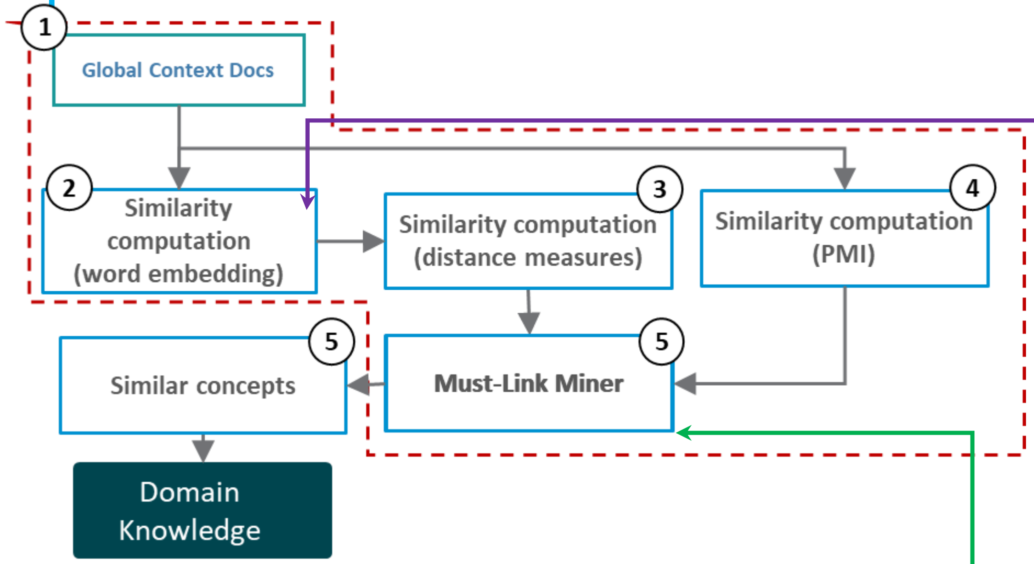
Algorithm 4 : Must link mining algorithm

Input : Word embedding vector $\vec{V}$
Result: must link M_{link}

```
Vocabulary voc ← getVocabular(V⃗)
foreach (document w_i ∈ voc) do
    sim(w_i, w_{i+1}) = V⃗_wi V⃗_wi+1 / (|V⃗_wi||V⃗_wi|)
    PMI(w_i, w_{i+1}) = log( P(w_i, w_{i+1}) / (P(w_i)P(w_{i+1})) )
    r(w_i, w_{i+1}) = PMI(w_i, w_{i+1}).sim(w_i, w_{i+1})
    if (r(w_i, w_{i+1}) >= 1) then
        M_link + − = w_i
    end
end
return M_link
```

UX | Solution 2-2: Knowledge Mining (3/4)

Topic Extractor → **Knowledge Mining**



$$\boldsymbol{\lambda}_{w_1,w_2} = \begin{cases} 1, & \textit{Same word} \\ r(w_1, w_2) > 1 & \textit{is a must} - \textit{link} \\ 0, & \textit{Other wise} \end{cases}$$

Algorithm 3 : Word embedding vector generation algorithm

Input : Global Context Corpus $C_d = \{d_1, d_2, d_3, ..., d_n\}$, Context Window c
Result: Word Embedding Vector V

```
Word embedding Vector V⃗
foreach (document D ∈ C_d) do
    foreach (word w ∈ D) do
        Compute P(W_{x+c}|W_x) = exp(vwx.vwx) / Σ_{w=1}^{V} exp(vw.vwx)
        V⃗ ← P(W_{x+c}|W_x)
    end
end
return V⃗
```

Algorithm 4 : Must link mining algorithm

Input : Word embedding vector $\vec{V}$
Result: must link M_{link}

```
Vocabulary voc ← getVocabular(V⃗)
foreach (document w_i ∈ voc) do
    sim(w_i, w_{i+1}) = (V⃗_{wi} V⃗_{wi+1}) / (|V⃗_{wi}||V⃗_{wi}|)
    PMI(w_i, w_{i+1}) = log( P(w_i, w_{i+1}) / (P(w_i)P(w_{i+1})) )
    r(w_i, w_{i+1}) = PMI(w_i, w_{i+1}).sim(w_i, w_{i+1})
    if (r(w_i, w_{i+1}) >= 1) then
        M_link + − = w_i
    end
end
return M_link
```

Contributions

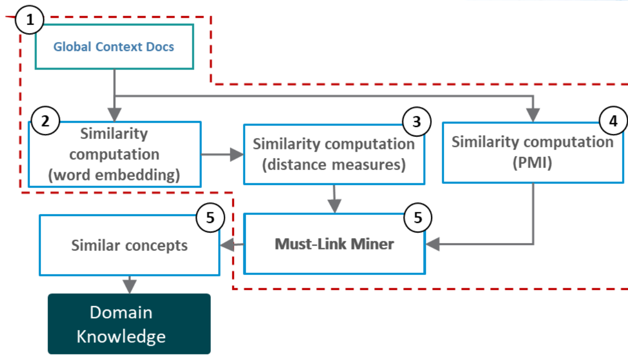
- A novel data representation for topic modeling based on syntactic and semantic relationships derived from distances calculated within a pre-trained word embedding space

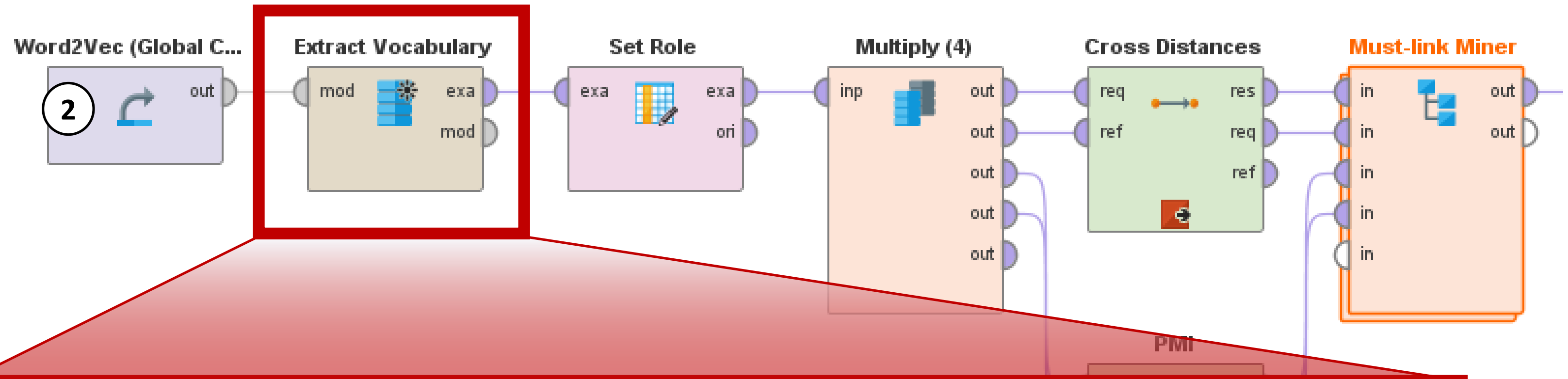
Related Publication

- Hussain, Jamil, and Sungyoung Lee. "Mining user experience dimensions from mental illness apps." International Conference on Smart Homes and Health Telematics. Springer, Cham, 2017.

UX Solution 2-2: Knowledge Mining (3/4)

Similarity computation (distance measures)

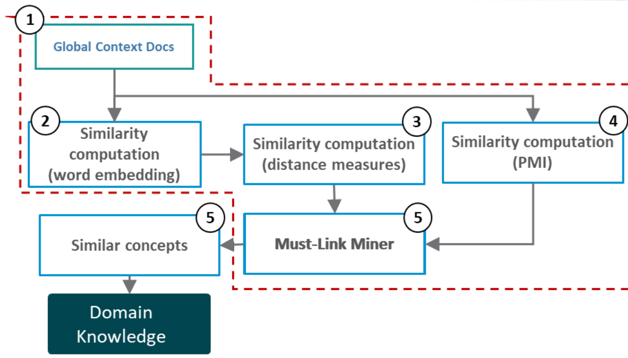


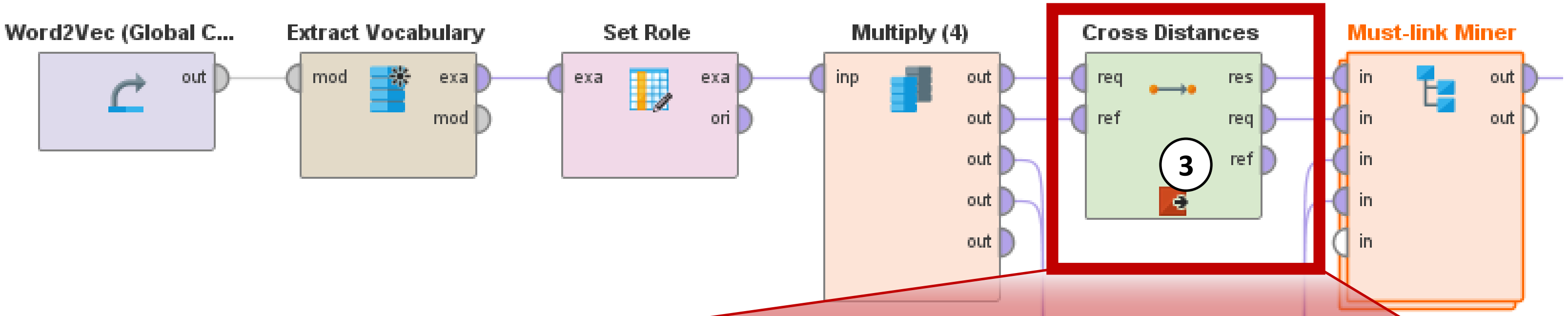


Row No.	word	dimension_0	dimension_1	dimension_2	dimension_3	dimension_4	dimension_5	dimension_6	dimension_7	dimension_8	dimension_9
1	content	0.194	0.497	0.352	0.581	0.245	0.335	0.060	0.244	-0.130	0.043
2	hotel	0.241	0.549	-0.187	0.100	0.553	0.423	-0.076	0.272	-0.005	-0.175
3	room	0.216	0.262	0.430	-0.154	0.526	0.220	0.322	-0.067	-0.289	0.400
4	stay	0.082	0.516	0.151	0.343	0.285	0.230	-0.003	0.615	-0.021	0.272
5	stayed	0.159	0.724	0.316	0.078	-0.196	0.212	-0.011	0.459	0.079	0.210
6	rooms	-0.019	0.528	-0.016	-0.086	0.276	0.285	0.216	0.708	-0.053	0.074
7	staff	0.055	0.591	0.383	0.375	0.387	0.054	-0.177	0.400	0.011	-0.127
8	clean	0.284	-0.163	-0.158	-0.228	0.430	0.398	-0.120	0.429	0.490	0.185
9	night	-0.431	-0.212	-0.292	-0.403	0.390	0.219	0.059	-0.304	0.211	0.424
10	area	0.237	-0.515	0.448	0.050	-0.190	-0.217	-0.078	-0.305	-0.454	-0.295
11	day	-0.072	0.419	0.198	-0.558	0.488	0.019	-0.354	0.264	0.185	0.030
12	great	0.227	-0.076	0.288	-0.624	0.139	0.286	-0.475	0.022	-0.010	-0.378
13	time	-0.120	0.096	0.371	0.486	0.053	0.085	-0.536	0.445	-0.232	-0.231

UX Solution 2-2: Knowledge Mining (3/4)

Similarity computation (distance measures)

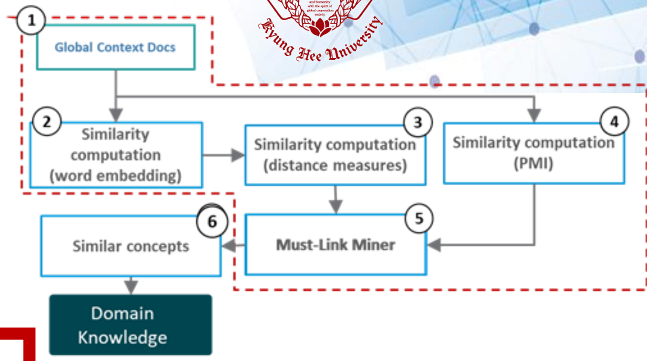


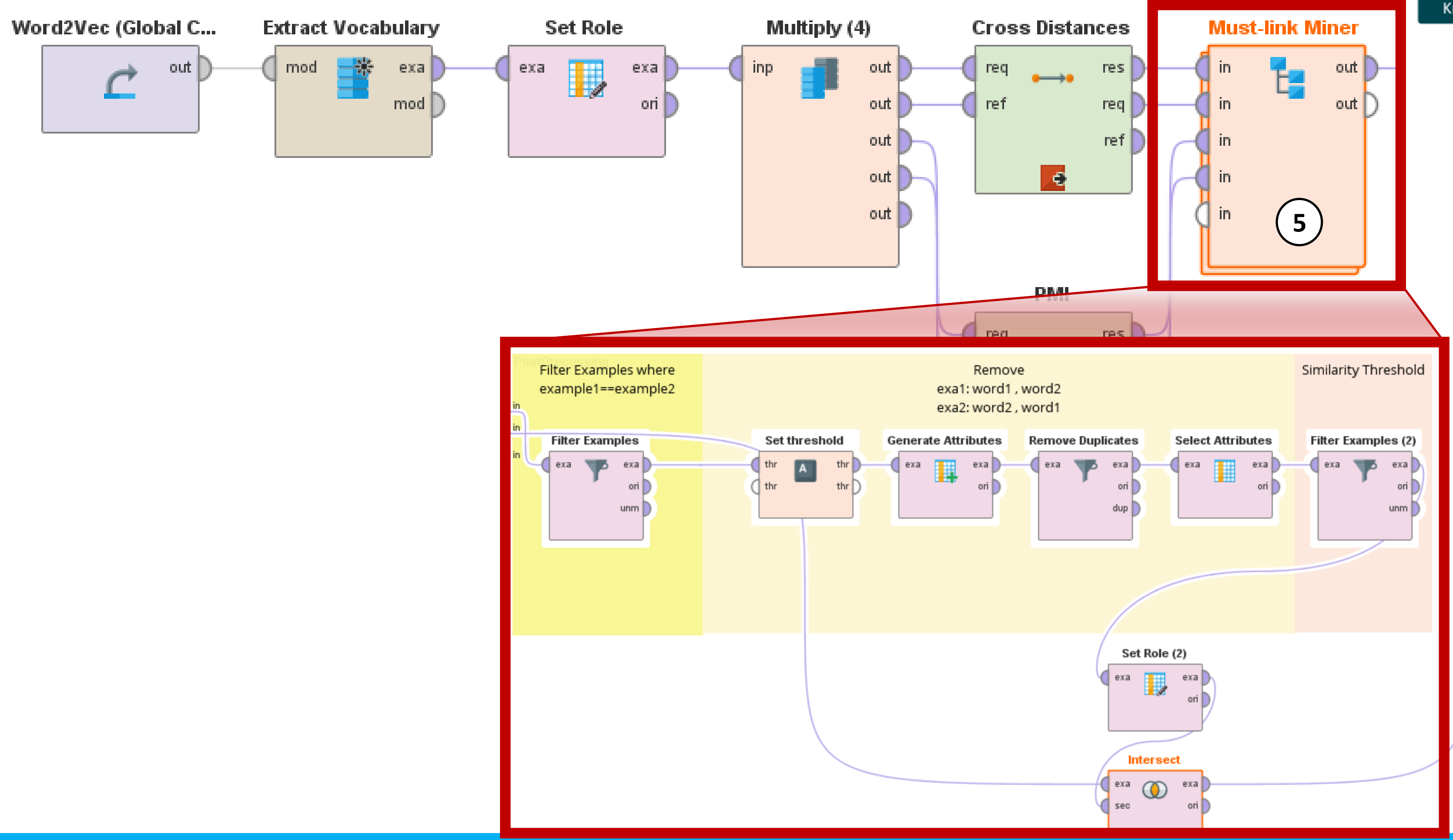


Row No.	request	document	distance
1	area	take	-0.921
2	take	area	-0.921
3	shower	top	-0.885
4	top	shower	-0.885
5	called	happy	-0.855
6	happy	called	-0.855
7	lounge	typical	-0.846
8	typical	lounge	-0.846
9	helpful	finally	-0.824

Prof. Tae-Seong Kim (Query 1)

Similarity computation (distance measures)





UX | Solution 2-2: Knowledge Mining (4/4)

Topic Extractor - **Knowledge Mining** - **Example**

$$p(w_{x+c}|w_x) = \frac{\exp(\mathbf{v}_{w_{x+c}} \cdot \mathbf{v}_{w_x})}{\sum_{w=1}^{V} \exp(\mathbf{v}_w \cdot \mathbf{v}_{w_x})}$$

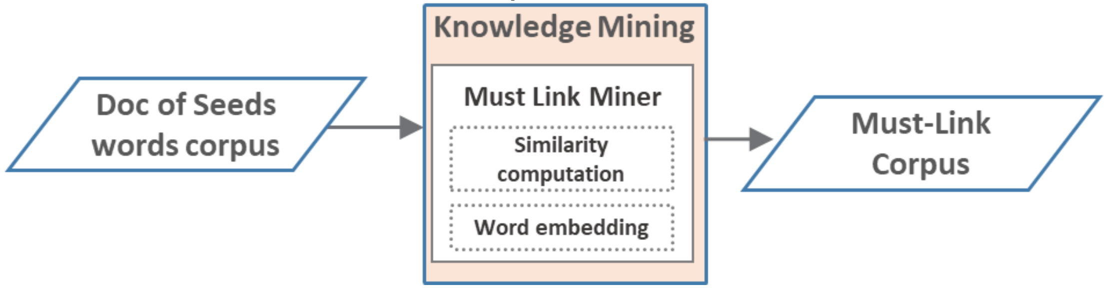
$$PMI(w_1, w_2) = \log \frac{P(w_1, w_2)}{P(w_1)P(w_2)}$$

$$P(w) = \frac{\#D(w)}{\#D}$$

$$sim(w_1, w_2) = \frac{\vec{v}_{w_1}\vec{v}_{w_2}}{|\vec{v}_{w_1}|\,|\vec{v}_{w_1}|}$$

$$P(w_1, w_2) = \frac{\#D(w_1, w_2)}{\#D}$$

- **Must-link Miner using similarity computation**
  1. **Word embedding (Skip-Gram)**
  2. **Cosine similarity**
  3. **Point-wise Mutual Information (PMI) -** μ



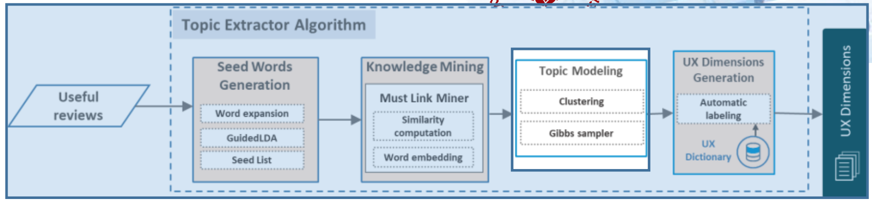
$$\boldsymbol{\lambda}_{w_1, w_2} = \begin{cases} 1, & Same\ word \\ r(w_1, w_2) > 1 & is\ a\ must-link \\ 0, & Other\ wise \end{cases}$$

Some example must-links.

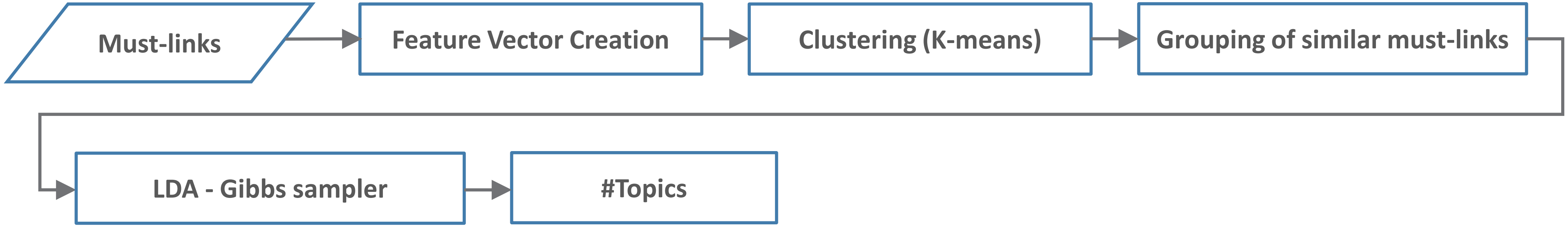
w_1	w_2	Sim(w_1, w_2)	PMI(w_1, w_2)	$r(w_1, w_2)$= PMI(w_1, w_2) X Sim(w_1, w_2)
Warranty	Repair	0.820	3.153	2.585
Windows	XP	0.762	4.789	3.649

Solution 2-2 : Topic Modeling (1/2)

Topic Extractor - **Topic Modeling**



- **Integration of must-link into the Gibbs sampler**
  1. **Feature vector creations**
  2. **Clustering**

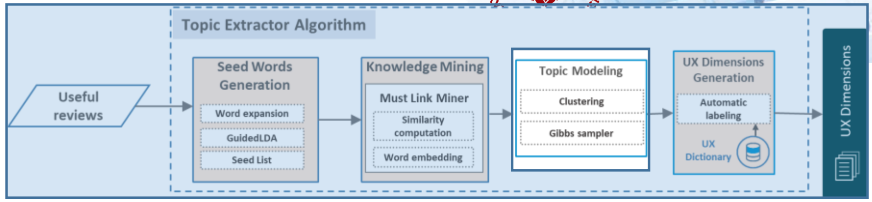


$$P(z_i = k | z_{-i}, \alpha, \beta, \lambda) \propto \frac{n_{dk} + \alpha}{n_d + T\alpha} \times \frac{\sum_{w'=1}^{V} \lambda_{k,w_i,w'} \times n_{kw'} + \beta}{\sum_{v=1}^{V} \left(\sum_{w'=1}^{V} \lambda_{k,v,w'} \times n_{kw'} + \beta \right)}$$

where z_i is the topic assignment of current word w_i . n_{dk} is the number of times topic k is assigned to a word in current document d. n_d is the length of document d. $n_{kw'}$ is topic-word counter, i.e., the number of times w' is assigned to topic k. α and β are predefined Dirichlet hyper-parameters. $\lambda_{k,wi,w'}$ is the word relatedness of a must-link w_i and w' which has been grouped into group k. T is the number of topics, and V is the vocabulary size.

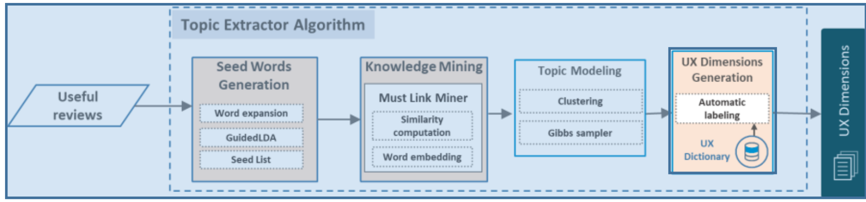
UX Solution 2-2 : Topic Modeling (2/2)

Topic Extractor - **Topic Modeling** - **Example**

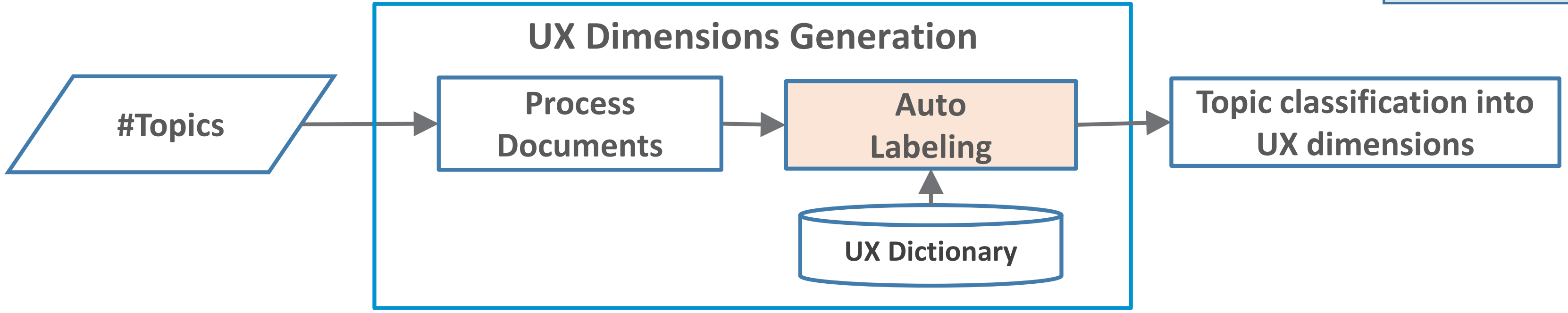


Topic 1		Topic 2		Topic 3		Topic n	
Word	**Weight**	**Word**	**Weight**	**Word**	**Weight**	**Word**	**Weight**
fun	89	accessible	50	visual	35	annoy	69
annoy	85	effective	48	effect	35	awful	64
creative	79	efficient	43	cute	33	awkward	59
enjoy	76	interface	43	trendy	33	confuse	44
exciting	71	reliable	41	technological	25	cheer	36
frustrate	67	usable	38	streamlined	23	rigid	35
addict	61	elegant	35	shape	22	okay	33
impressive	46	error	33	pleasurable	21	trust	26
cool	45	inconsistant	33	color	18	value	24
addict	37	delay	27	smooth	13	dislike	24
regret	34	load	27	beautiful	12	petty	23
cute	32	trouble	12	unusual	11	help	20
h13ate	32	bug	11	futuristic	9	hope	11

UX | Solution 2-3: UX Dimensions Generation (1/3)



Workflow of topic labeling into UX dimensions



- **In UX Dimensions Generation, we contributes in**
  - **UX existing aspects dictionary creation**, we intend to eliminate the manual selection of terms and ensure the objectivity of the choice of terms, used as gold UX dimensions.

Different to existing approaches

- Automatic labeling of generated topics based on existing UX dimensions

UX Solution 2-3: UX Dimensions Generation (2/3)

UX existing dimension dictionary

- Build the lexicons dictionary based on terms already used in previously validated scales [9] for measuring different aspects of UX using systematic review process.
- Finally selected the 223 terms, then applied the WordNet for word expression
  - Final thesaurus contains 500 terms by adding the synonyms

Contributions

- UX Dimension Dictionary Creation

	Dimensions	Individual terms
Hassenzahl Attrakdiff Scale [14]	Pragmatic Quality	technical, human, complicated, simple, impractical, practical, cumbersome, direct, unpredictable, predictable, Confusing, clear, Unruly, manageable
	HQ-Stimulation	typical, original, standard, creative, cautious, courageous, conservative, innovative, lame, exciting, Easy, challenging, Commonplace, new
	HQ-Identification	isolating, integrating, amateurish, professional, gaudy, classy, cheap, valuable, non-inclusive, inclusive, unpresentable, presentable
	:	
psychometric scales [15]	Aesthetics	aesthetic, pleasant, clear, clean, symmetric, artistic creative, fascinating, special effects, original, sophisticated

UX Solution 2-3: UX Dimensions Generation (3/3)

Topic Extractor - **Topic Automatic Labeling** - **Example**

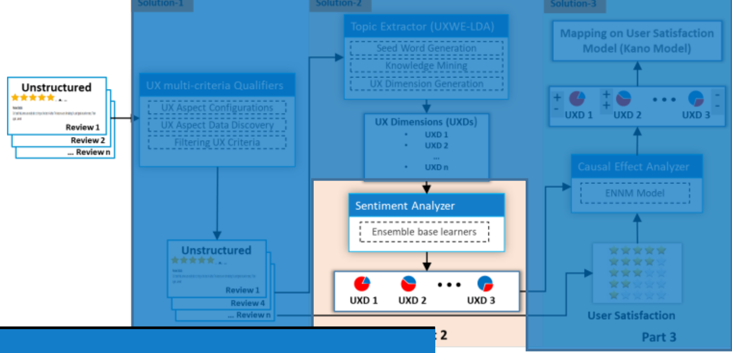
UX Dimensions

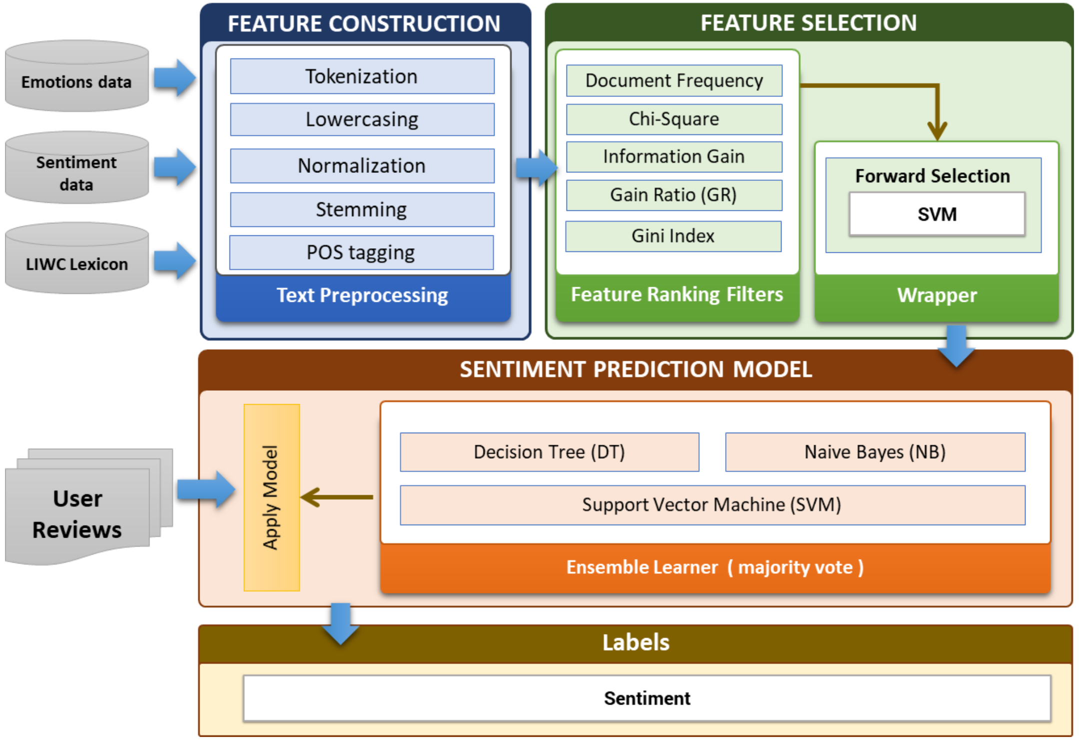
Hedonic | Effectiveness | Aesthetics | Affect

Topic 1		Topic		Topic 3		•••	Topic n	
Word	**Weight**	**Word**	**Weight**	**Word**	**Weight**		**Word**	**Weight**
fun	89	accessible	50	visual	35		annoy	69
annoy	85	effective	48	effect	35		awful	64
creative	79	efficient	43	cute	33		awkward	59
enjoy	76	interface	43	trendy	33		confuse	44
exciting	71	reliable	41	technological	25		cheer	36
frustrate	67	usable	38	streamlined	23		rigid	35
addict	61	elegant	35	shape	22		okay	33
impressive	46	error	33	pleasurable	21		trust	26
cool	45	inconsist	33	color	18		value	24
addict	37	delay	27	smooth	13		dislike	24
regret	34	load	27	beautiful	12		petty	23
cute	32	trouble	12	unusual	11		help	20
h13ate	32	bug	11	futuristic	9		hope	11

UX Solution 2-4: Sentiment Analyzer

Sentiment orientation of extracted UX dimensions





Algorithm 5 : Feature Selection

Input : $D = \{d_1, d_2, d_3, \ldots d_n\}$; *# dataset D with n features*
$F = \{IG, MRMR, CHI, GR, GI\}$; *#set of statistical filters F*
λ: # threshold
t, k: #top K

Output: D^I: $\{d_1, d_2, d_3, \ldots d_k\}$, *#top K highest ranked features*

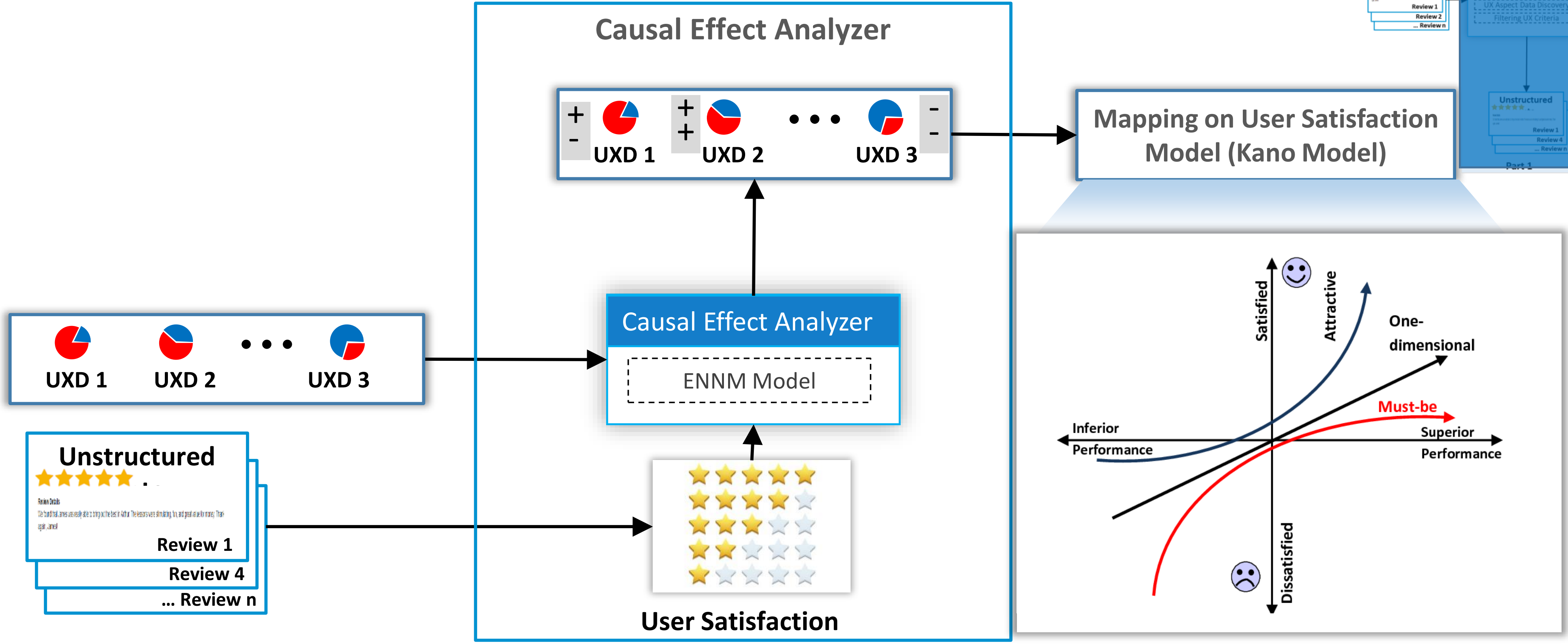
Initialize
$R_F \leftarrow$ *new Set(); #initialize ranked feature set*
for f in F **do**
  $X_F \leftarrow$ **rankedFeatures**(D, *f*); *# apply statistical filter f on D*
  $X_F \leftarrow$ **sortDESC**(X_F); *#sort ranked features in DESC order*
  $T_F \leftarrow$ **selectTopKFeatures**(X_F, k); *#select top k features*
R_F.**add**(T_F);*# add top K features to feature set R_F*
endfor
$C_F \leftarrow$ **majorityVoting**(R_F, $\lambda \geq t$) *#apply majority voiting and select common features with $\lambda \geq$ t*
$D^I \leftarrow$ **selectTopKFeatures**(C_F, k) *#select top k features*
Return D^I;

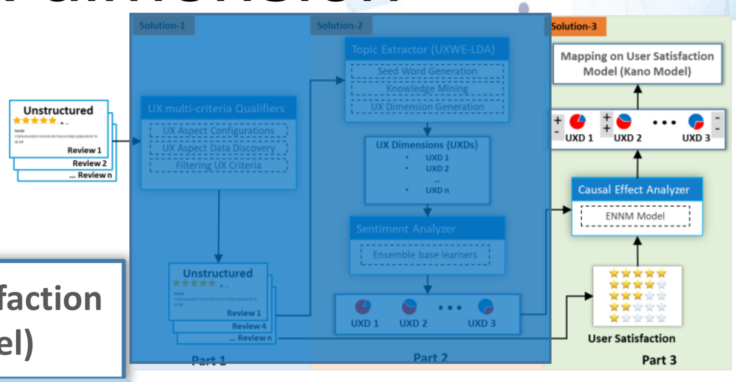
Related Publication

- Hussain, Jamil, et al. "A multimodal deep log-based user experience (UX) platform for UX evaluation." Sensors 18.5 (2018): 1622.
- Jawad, Jamil Hussain, et al "EnSWF: effective features extraction and selection in conjunction with ensemble learning methods for document sentiment classification"

UX Solution 3: Measuring the effects on each UX dimension

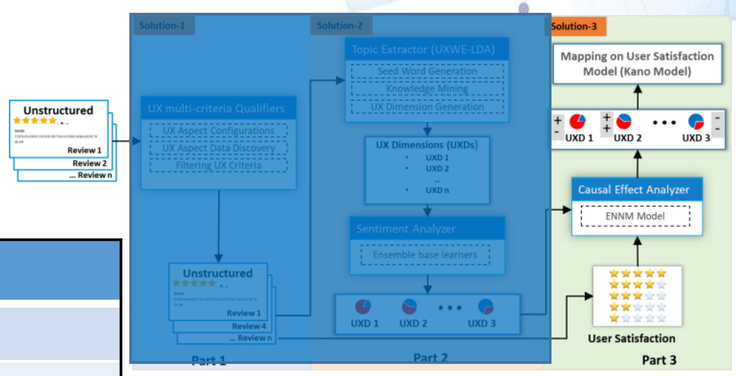
Overview





UX Solution 3: Causal Effect Analyzer

Ensemble neural network based model (ENNM) [26]

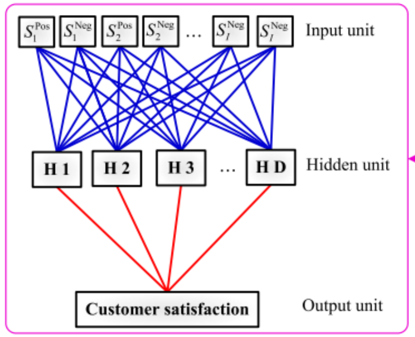


Structure data of online reviews

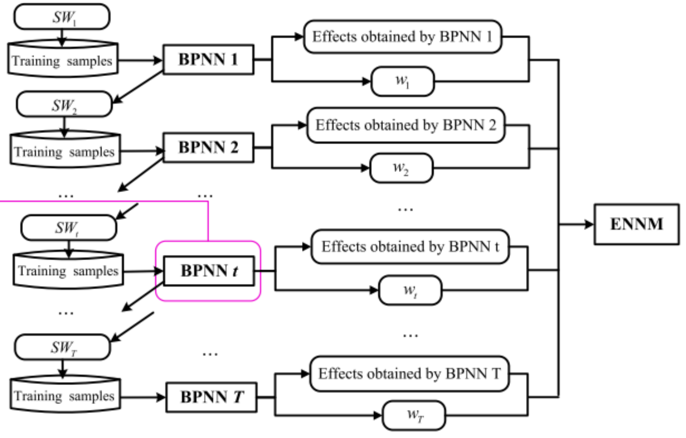
Online reviews	UX Dimensions (UXDs)						
	D_1		D_2			D_n	
	Pos	Neg	Pos	Neg	…	Pos	Neg
r1	1	0	0	1	…	0	0
r2					…	0	1
…	…	…	…	…	…	…	…
R3	0	1	1	0	…	1	0

Benefits of ENNM

- The neural networks (NNs) are a powerful approach for prediction tasks, which outperform multiple regression models in terms of data fitting in situations where non-normal data, non-linearities, and multicollinearity relationship are present

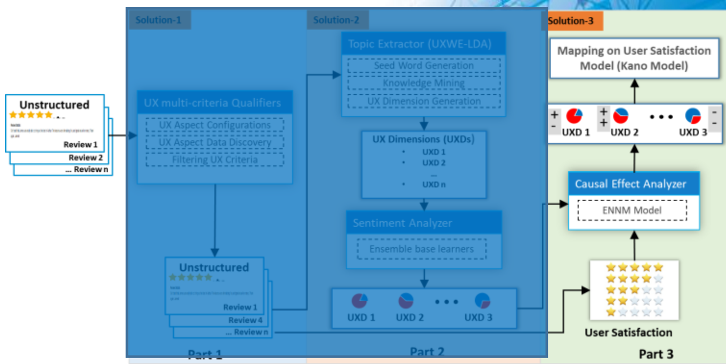


The structure of BPNN t



26. Bi, J.W. et al. 2019. Modelling customer satisfaction from online reviews using ensemble neural network and effect-based Kano model. *International Journal of Production Research*. 0, 0 (2019), 1–21.

Solution 3: Causal Effect Analyzer



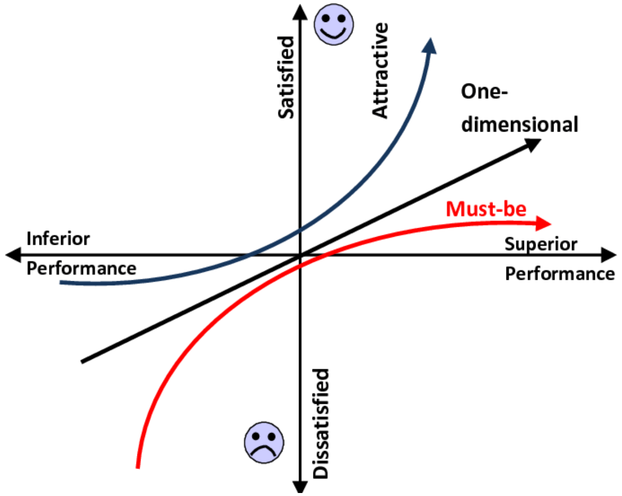
Mapping the effects on user satisfaction Model (Kano Model)

ENNM Generated Data

UXDS	W_i^{pos}	W_i^{neg}
f_1	0.14	-0.19
f_2	0.19	-0.14
f_3	-0.19	-0.17
f_4	-0.25	-0.27
f_5	0.08	0.25
f_1	-0.37	-0.26
…	…	…
f_n	0.14	0.15

Mapper

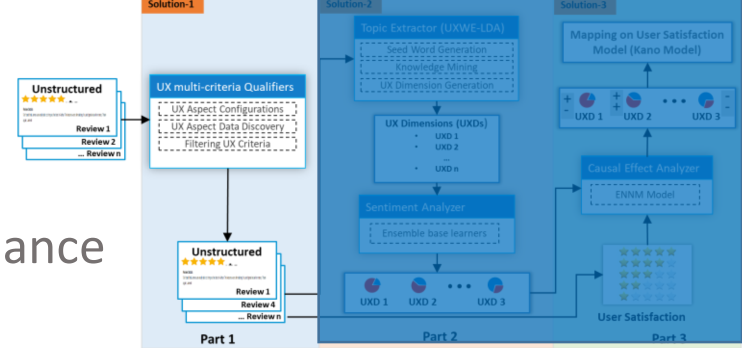
Mapping Rules



if $\bar{W}_i^{\mathrm{Pos}} \le 0$ and $\bar{W}_i^{\mathrm{Neg}} < 0$, then f_i is a must-be
if $\bar{W}_i^{\mathrm{Pos}} \le 0$ and $\bar{W}_i^{\mathrm{Neg}} \ge 0$, then f_i is a reverse
if $\bar{W}_i^{\mathrm{Pos}} > 0$ and $\bar{W}_i^{\mathrm{Neg}} < 0$, then f_i is a performance
if $\bar{W}_i^{\mathrm{Pos}} > 0$ and $\bar{W}_i^{\mathrm{Neg}} \ge 0$, then f_i is an excitement

Contributions

- A methodology for autonomously classifying extracted aspects from textual data into Kano Model categories using rule base approach.



UX Experimental Results

Solution 1: UX multi-criteria Qualifiers(UXMCQ) → Classification Performance

Experimental Setup

Datasets: For aspect category classification, we use the dataset from[20] which contains restaurant reviews labelled with domain-related aspects (e.g., food, staff, ambience) in English.
Evaluation metric: Precision, Recall and F-Measure

Method	Aspects											
	Staff			Food			Ambiance			Overall		
	Pre.	Rec.	F1	Pre.	Rec.	F1	Pre.	Rec.	F1	Pre.	Rec.	F1
LocLDA	**0.80**	0.59	0.68	0.90	0.65	0.75	0.60	0.68	0.64	0.77	0.64	0.69
ME-LDA	0.61	0.54	0.64	0.87	**0.79**	**0.83**	**0.77**	0.56	**0.65**	**0.81**	0.63	0.70
UXMCQ	0.78	**0.86**	**0.71**	**0.96**	0.69	0.81	0.55	**0.75**	0.63	0.70	**0.77**	**0.72**

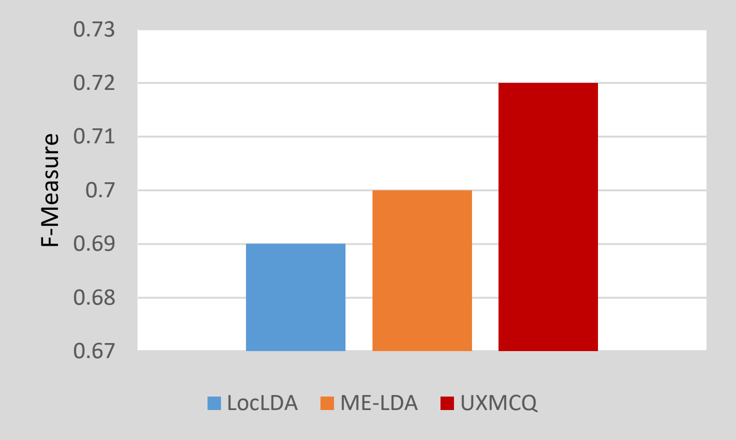
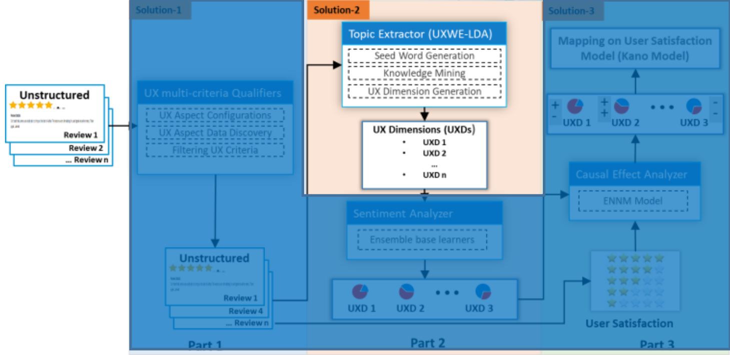


Figure 1: Overall F-Measure of proposed method

Discussion on results

The results shows the experiment and a comparison with the other systems. Despite not requiring human intervention to relabel the obtained topics unlike the other two systems, UXMCQ achieves slightly better overall performance

UX Experimental Results



Solution 2: UXWE-LDA model

- **Datasets:** Datasets from **Chen and Liu** [12].
  - **Electronic products or domains**
  - **Non- electronic products or domains**
- **Setting:** For comparison, we use the following parameter settings
  - α=1, B=0.1, number of topics T=15, context window=5, Top n words=30
- **Software and languages**: Windows 7, Mallet, Rapid Miner, KNIME, Genism toping modeling, Java, and Python NLTK library
- **Evaluation metric:** Topic coherence (UMass Topic Coherence [13])
- We performs different experiments to evaluates the proposed UXWE-LDA model and compares it with four state-of-the-art baseline models:
  - **LDA**
  - **WE-LDA**
  - **LF-LDA**
  - **LTM**

UX Experimental Results

Solution 2: Similarity Computation for topic and words selection

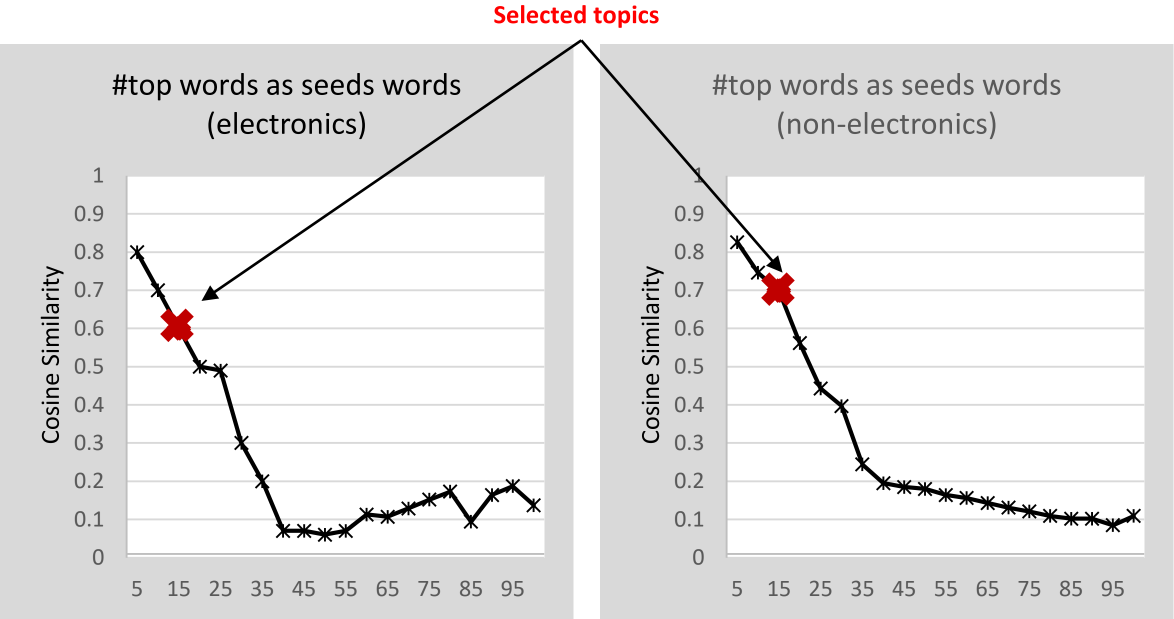


Figure 2: Average cosine similarity per the number of topics on electronic products dataset (top) and non-electronic products dataset (bottom).

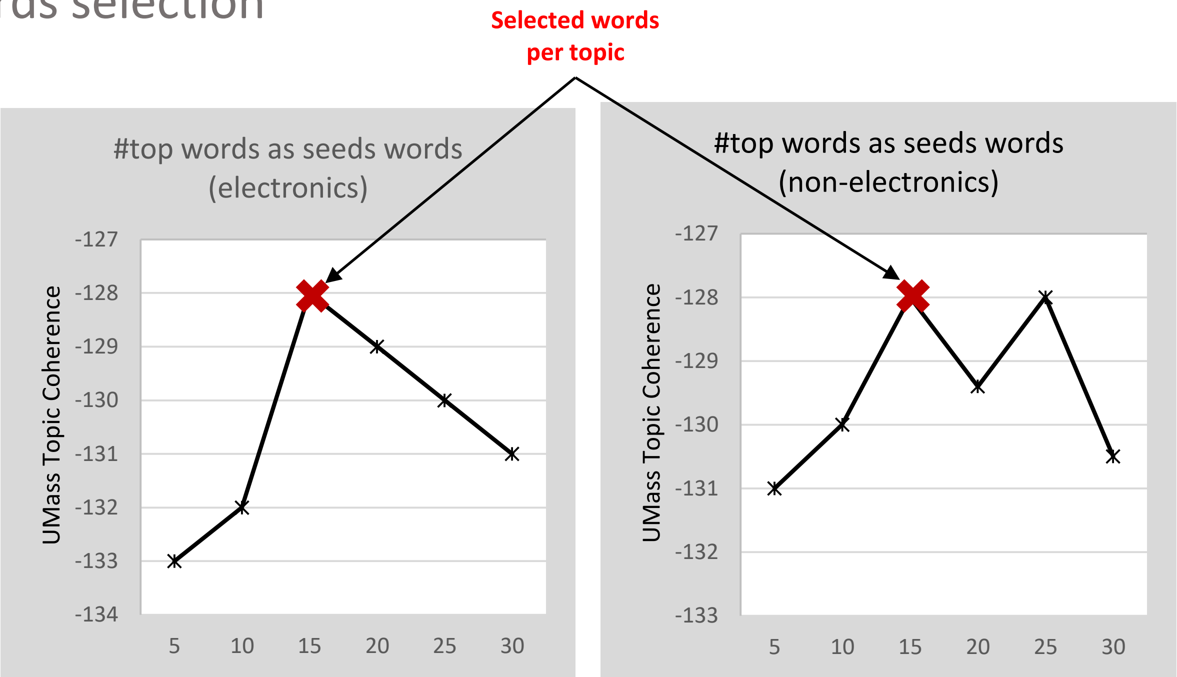


Figure 3: Average Topic Coherence of top 10 words with different number of seed words on electronic products dataset (top) and non-electronic products dataset (bottom).

Result Analysis

We selected the number of topic is 15 based on the their average cosine similarity

Result Analysis

We selected the top 15 words as seeds word due to higher topic coherences

UX Experimental Results

Solution 2: UXWE-LDA model comparison based on average topic coherence

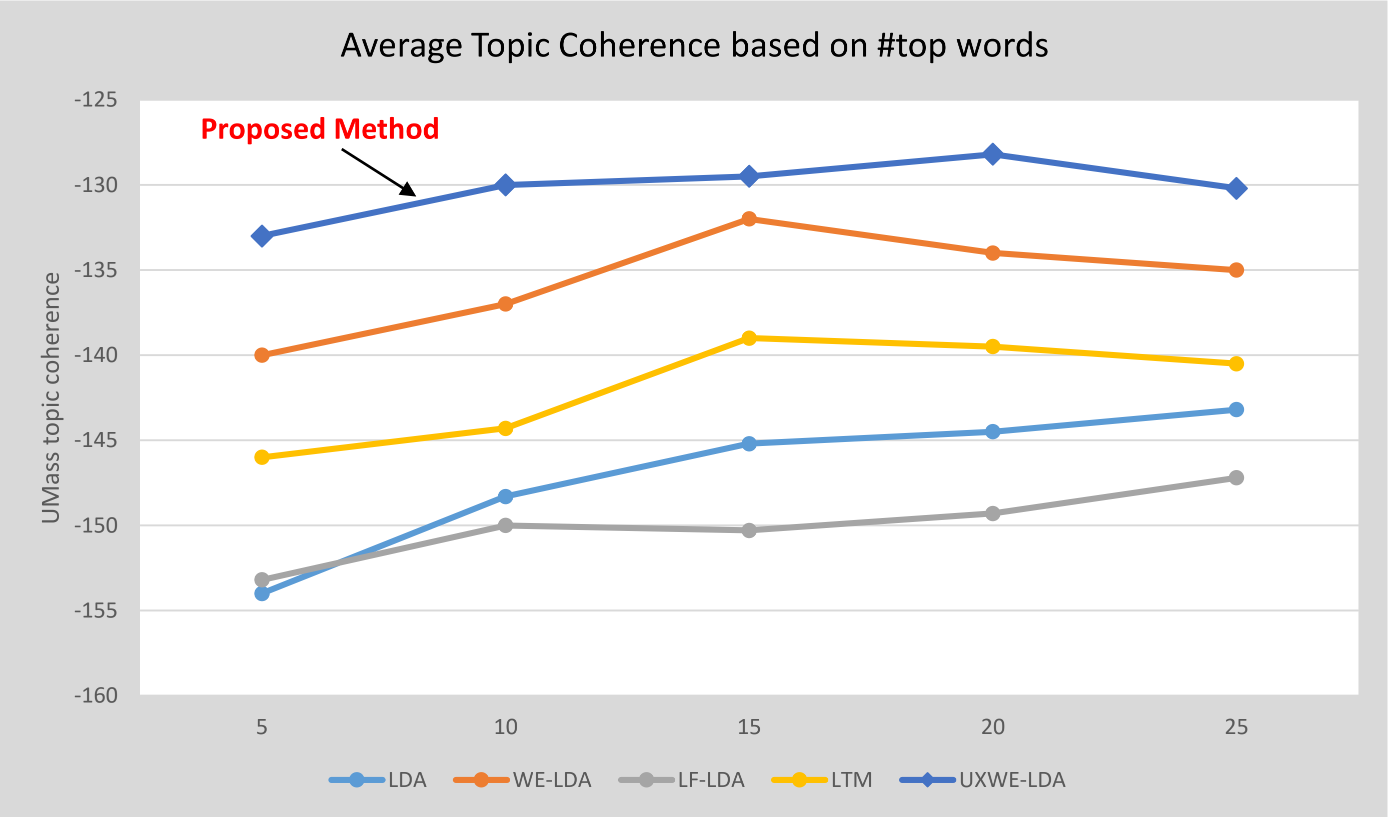


Figure 4: Average Topic Coherence of top 10 words with different number of topics on electronic products dataset

Discussion on results

The shows the average Topic Coherence of each model given different number of topics on electronic datasets. We note that given different number of topics, **UXWE-LDA** consistently achieves **higher Topic Coherence scores** than the baseline models on electronic datasets, which shows the proposed method is robust with different number of **must-link clusters.**

The overall coherence scores show an improvement 4 times over the existing methods

UX Experimental Results

Solution 2: UXWE-LDA model comparison based on model performance

$$F_1\ Score\ for\ topic\ k = 2 \times \frac{precision_k \times recall_k}{precision_k + recall_k}$$

Experimental Setup

Datasets: Google apps reviews [27]
Method: The human experts annotated by a total of **300 online reviews**, where each sentence is label based on the **provided UX dimension list.** **Mutually agreed sentence** all three annotators were considered as **gold-label** for the performance evaluation.
Evaluation metric: Precision, Recall , and F-measure

Topics	LDA			UXWE-LDA		
	Precision	Recall	F-measure	Precision	Recall	F-measure
attractiveness	0.71	0.46	0.55	0.83	0.72	0.77
dependability	0.78	0.49	0.60	0.80	0.91	0.85
efficiency	0.73	0.60	0.66	0.76	0.77	0.76
perspicuity	0.80	0.47	0.59	0.80	0.72	0.76
novelty	0.76	0.51	0.61	0.81	0.76	0.78
stimulation	0.75	0.47	0.58	0.87	0.81	0.84

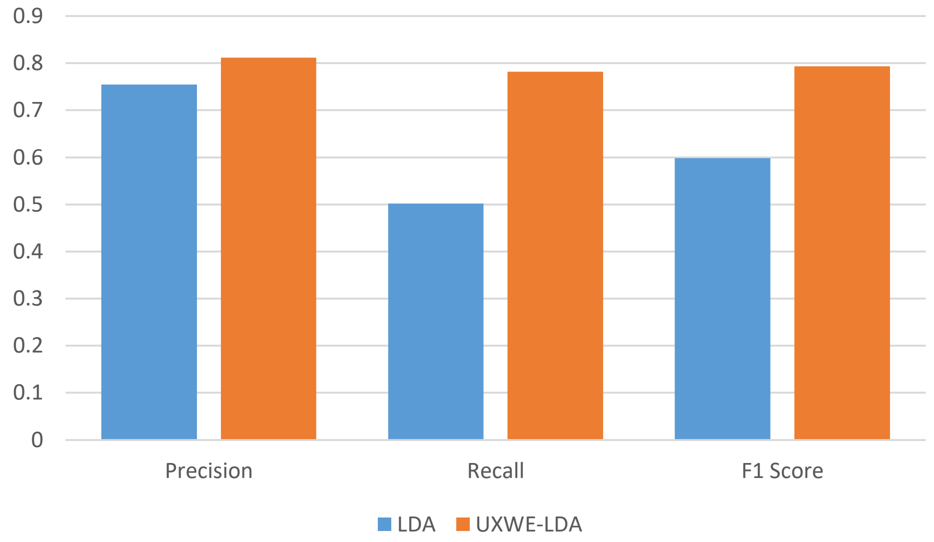


Figure 5: Average F-measure, Precision and Recall of LDA and UXWE-LDA.

Discussion

Where higher F1 score indicates, the model performs well for classifying the test data.

UX Experimental Results

Solution 2: UXWE-LDA model comparison based on log likelihood and Perplexity

Experimental Setup

Evaluation metric: log likelihood, Perplexity and Model Precision (word Intrusion) [28]

#Topics	LDA		WE-LDA		LF-LDA		UXWE-LDA	
	log likelihood	Perplexity	log likelihood	Perplexity	log likelihood	Perplexity	log likelihood	Perplexity
5	-7.3214	**784.38000**	-7.33350	788.58000	-7.33840	796.43000	**-7.13320**	936.58000
10	-7.2761	778.24000	-7.26470	762.16000	**-7.21340**	785.05000	-7.43850	**770.30000**
15	-7.2477	777.32000	-7.24670	755.55000	-7.23820	970.36000	**-7.38720**	**752.46000**

Model Precision(word Intrusion)

$$\mathrm{MP}_k^m = \sum_s \mathbb{1}(i_{k,s}^m = \omega_k^m)/S.$$

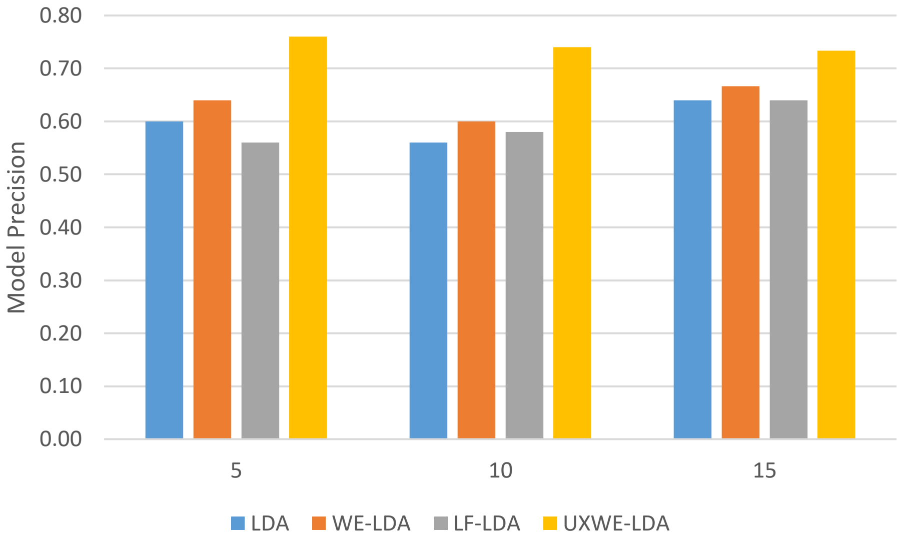
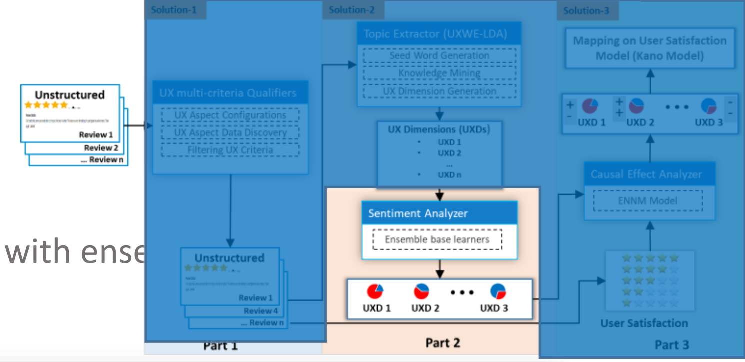


Figure 6: Model Precision based on the word intrusion task measures

UX Experimental Results



Solution 2: Sentiment Analyzer (effective features extraction and selection in conjunction with ense

Experimental Setup

Datasets: Cornell movie review dataset [23] 2. Amazon product reviews datasets [24]

Evaluation metric: Accuracy

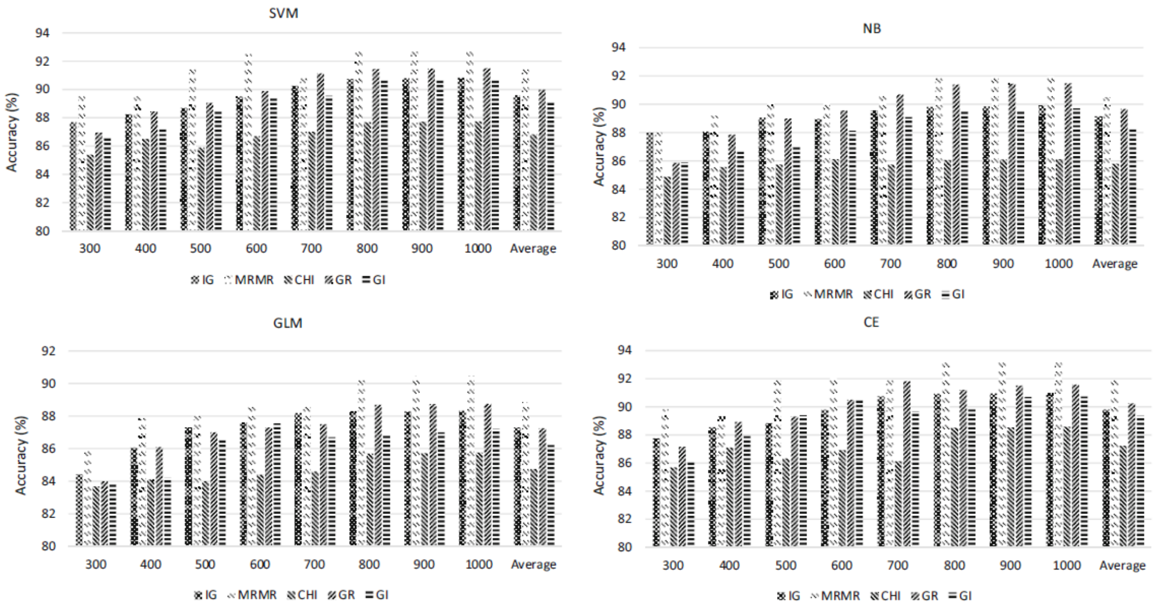
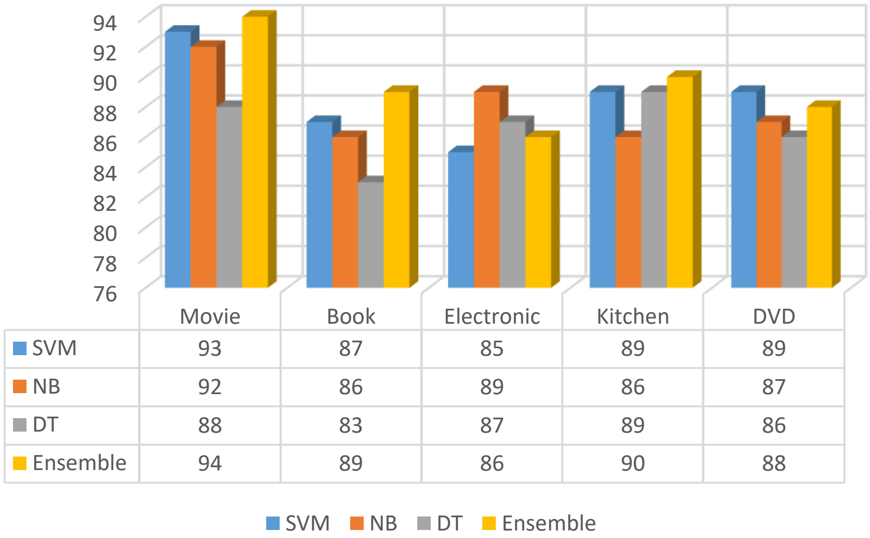


Figure 8: Average accuracy of classifier based on wrapper and filters



	Movie	Book	Electronic	Kitchen	DVD
SVM	93	87	85	89	89
NB	92	86	89	86	87
DT	88	83	87	89	86
Ensemble	94	89	86	90	88

Figure 7: average classification performance on top k high ranked score feature utilizing wrapper and filters feature selection, ensemble learner

UX

Comparison

Expert base validation

Experimental Setup

Datasets: Google apps reviews [27]

Evaluation metric: $Jaccard\ coefficient$
-To check the degree of dimensions overlapping between automatic extraction using UXWE-LDA and human experts

Method

Each researcher selected 50 reviews randomly; finally, a total of 150 reviews selected for UXWE-LDA validation. We compared the UXDs extracted from UXWE-LDA with the UXDs extracted by the human experts for checking the reliability of the result generated by UXWE-LDA.

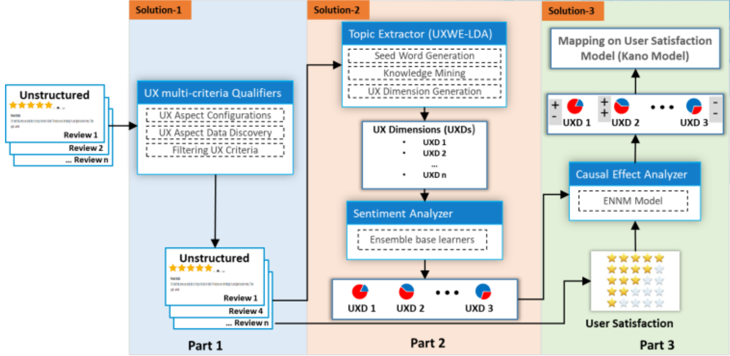
	JC
UXWE-LDA VS Human Expert 1	0.3
UXWE-LDA VS Human Expert 2	0.5
UXWE-LDA VS Human Expert 3	0.4

Dimensions	UXWE-LDA	Human Expert 1	Human Expert 2	Human Expert 3
Attractiveness	✓	X	✓	✓
Dependability	✓	✓	✓	✓
Efficiency	✓	X	✓	X
Perspicuity	✓	X	✓	✓
Novelty	✓	✓	✓	✓
Stimulation	✓	✓	X	X
Aesthetics	X	✓	X	✓
Complexity	X	✓	✓	✓
Affect and emotion	X	X	✓	X

Discussion

Due to complexity and ambiguity involves in UXDs extraction task from online reviews, the results show that UXWE-LDA is a reliable and suitable approach for UXDs extraction from online reviews.

$$Jaccard\ coefficient'(JC) = \frac{|D_{UXWE-LDA} \cap D_{Exp}|}{|D_{UX-WELDA} \cup D_{Exp}|}$$



UX Case Study 1 – Game Reviews dataset

User Satisfaction modeling based on the extracted UX dimension

Experimental Setup

Datasets: Games online reviews dataset [25]

Evaluation metric: Accuracy and topic coherence

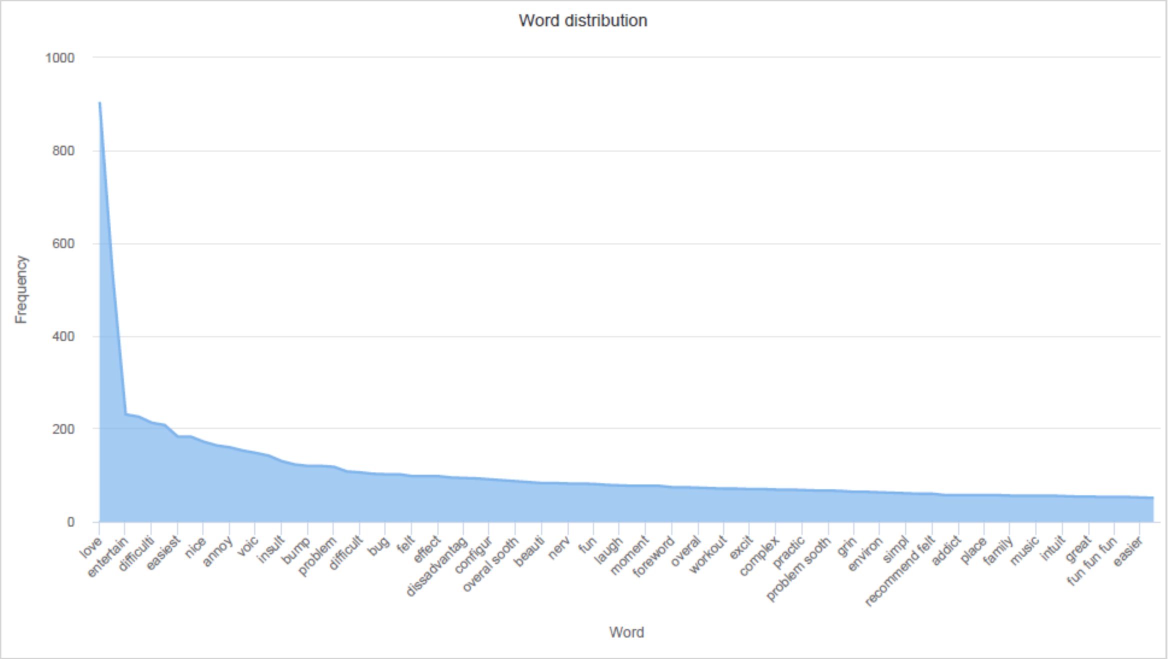


Figure 9: Word distribution for games reviews (n= 1 million)

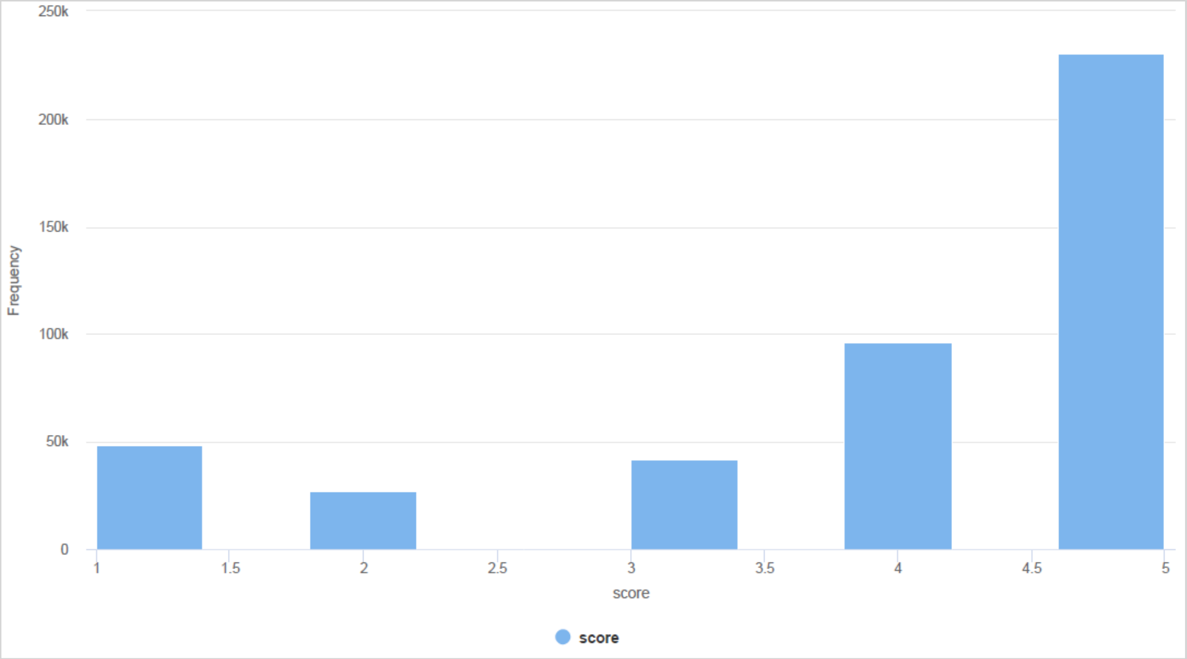


Figure 10: Overall user rating on reviews (n= 1 million)

UX | Case Study 1 – Game Reviews dataset

Extracted UX dimension and their sentiment orientation

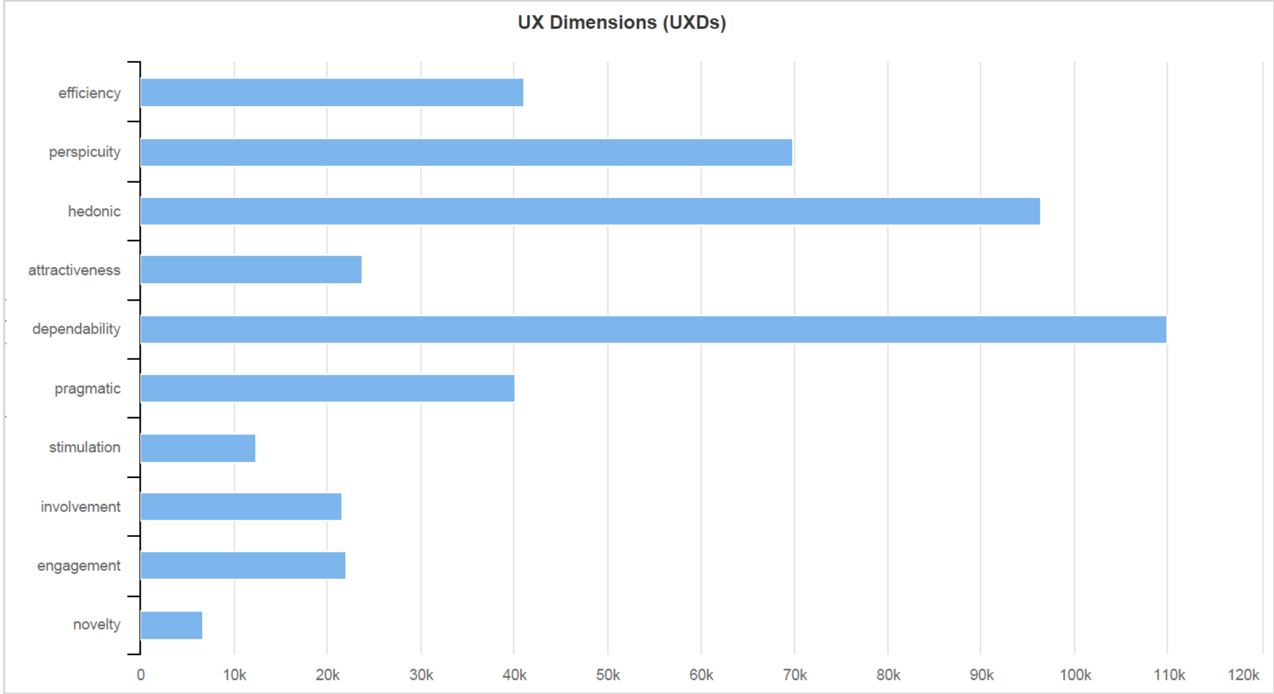


Figure 11: Extracted UX dimensions from user reviews

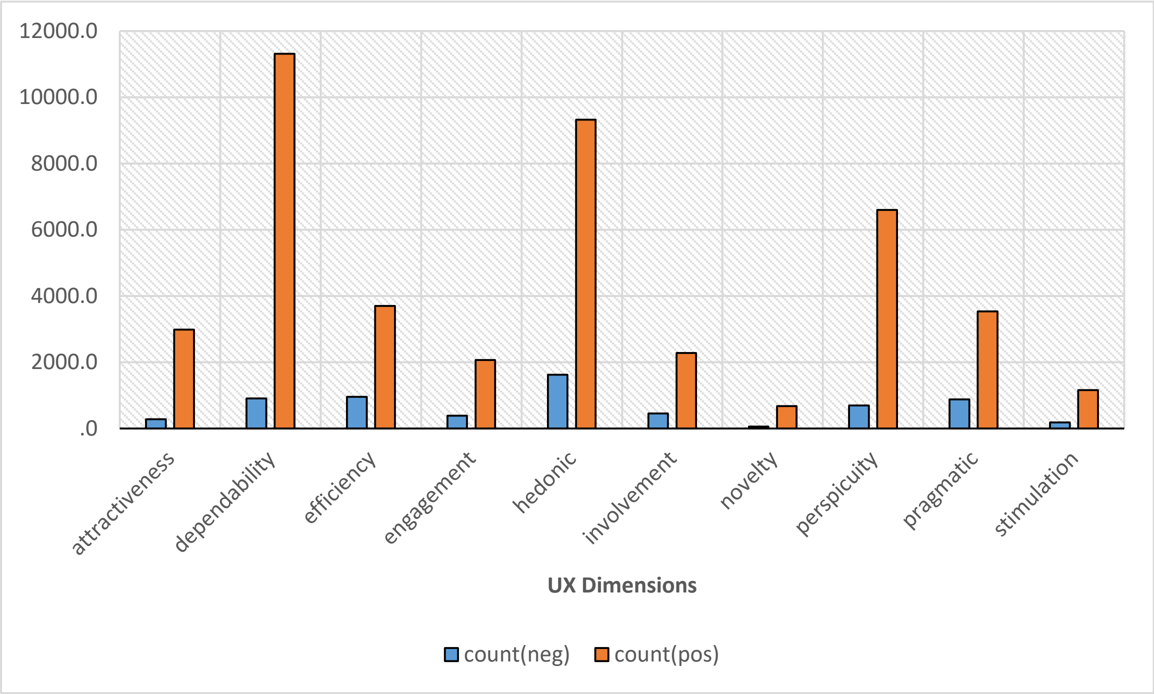
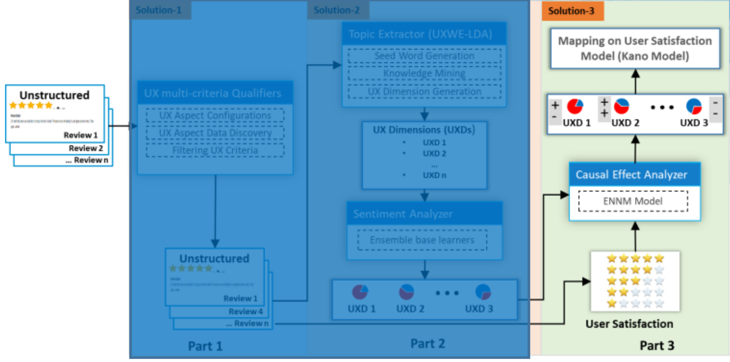


Figure 12: The results of the sentiment orientations of each UXD in all online reviews.

Case Study 1 – Game Reviews dataset

Classification results of UXDs of game data using ENNM on Kano Model



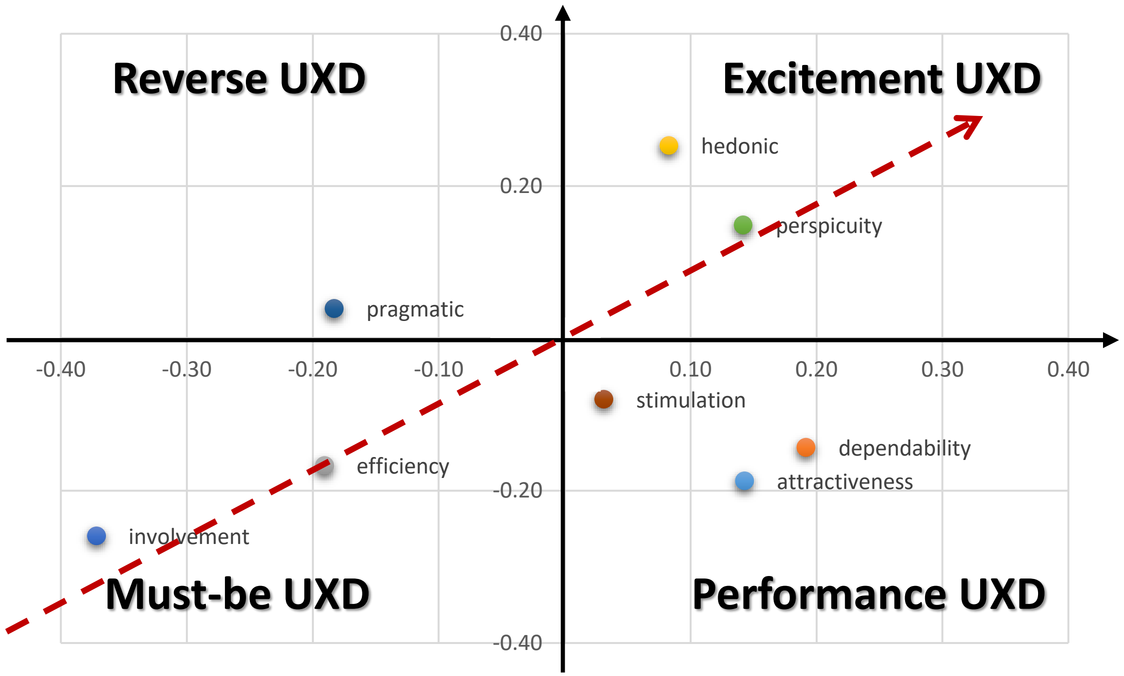
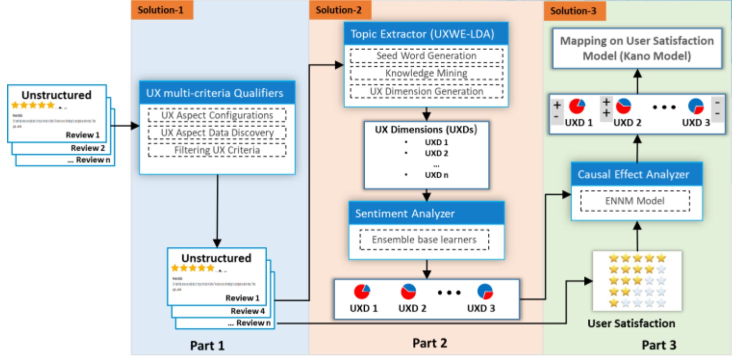


Figure 13: Mapping the extracted dimensions on Kano Model.

UXDS	W_i^{pos}	W_i^{neg}
attractiveness	0.14	-0.19
dependability	0.19	-0.14
efficiency	-0.19	-0.17
engagement	-0.25	-0.27
hedonic	0.08	0.25
involvement	-0.37	-0.26
perspicuity	0.14	0.15
pragmatic	-0.18	0.04
stimulation	0.03	-0.08



Case Study 2 – Google play-store(Apps Reviews)

User Satisfaction modeling based on the extracted UX dimension

Experimental Setup

Datasets: google play-store apps online reviews dataset [27]
Evaluation metric: Accuracy and topic coherence

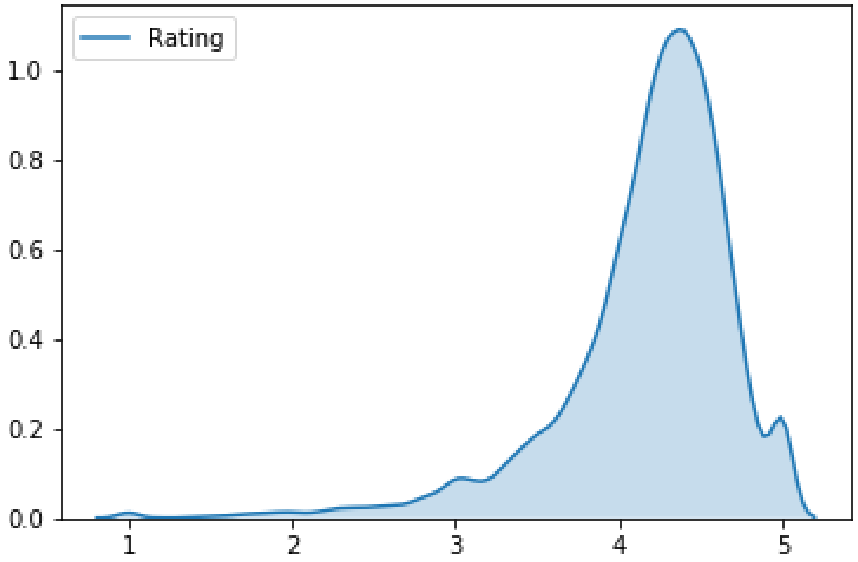


Figure 14: overall rating of user on online reviews

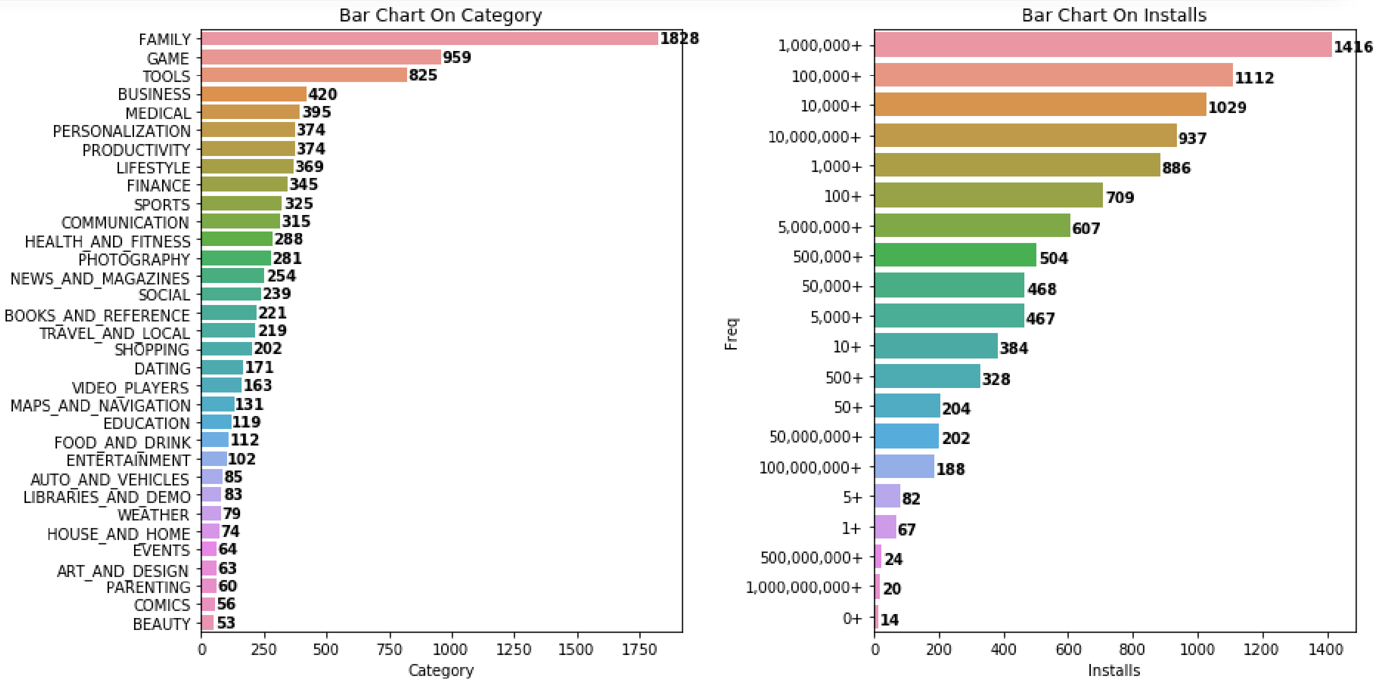
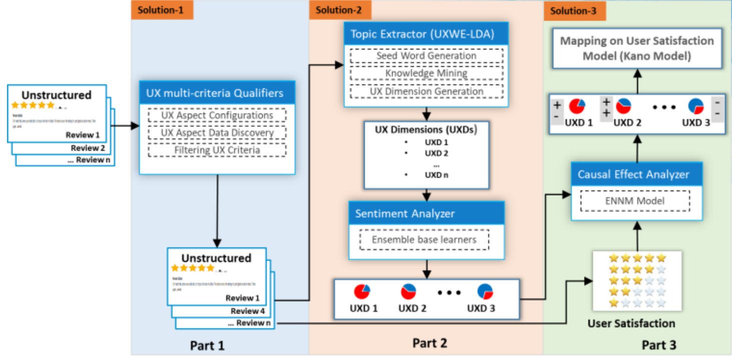


Figure 15: App Categories

Case Study 2 – Google play-store(Apps Reviews)

User Satisfaction modeling based on the extracted UX dimension



Experimental Setup

Datasets: google play-store apps online reviews dataset [27]

Evaluation metric: Accuracy and topic coherence

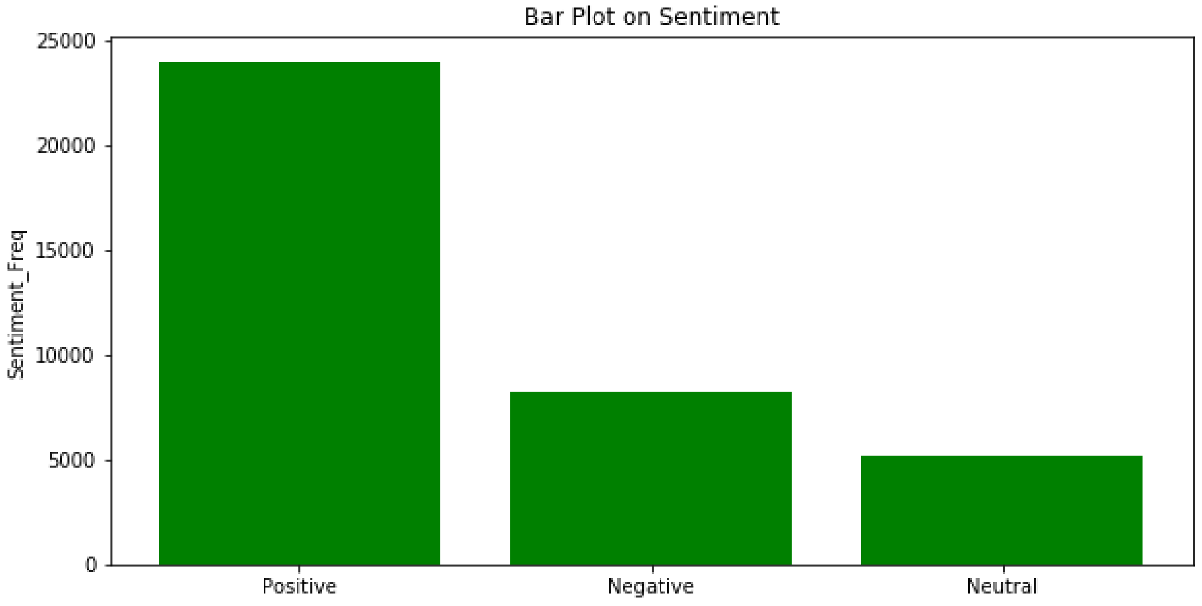


Figure 16: overall sentiment of user on online reviews

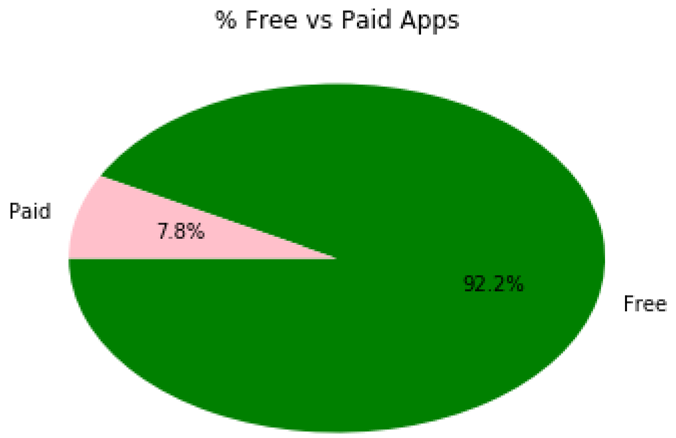


Figure 17: Apps distribution

UX Case Study 2 – Google play-store(Apps Reviews)

Extracted UX dimension and their sentiment orientation

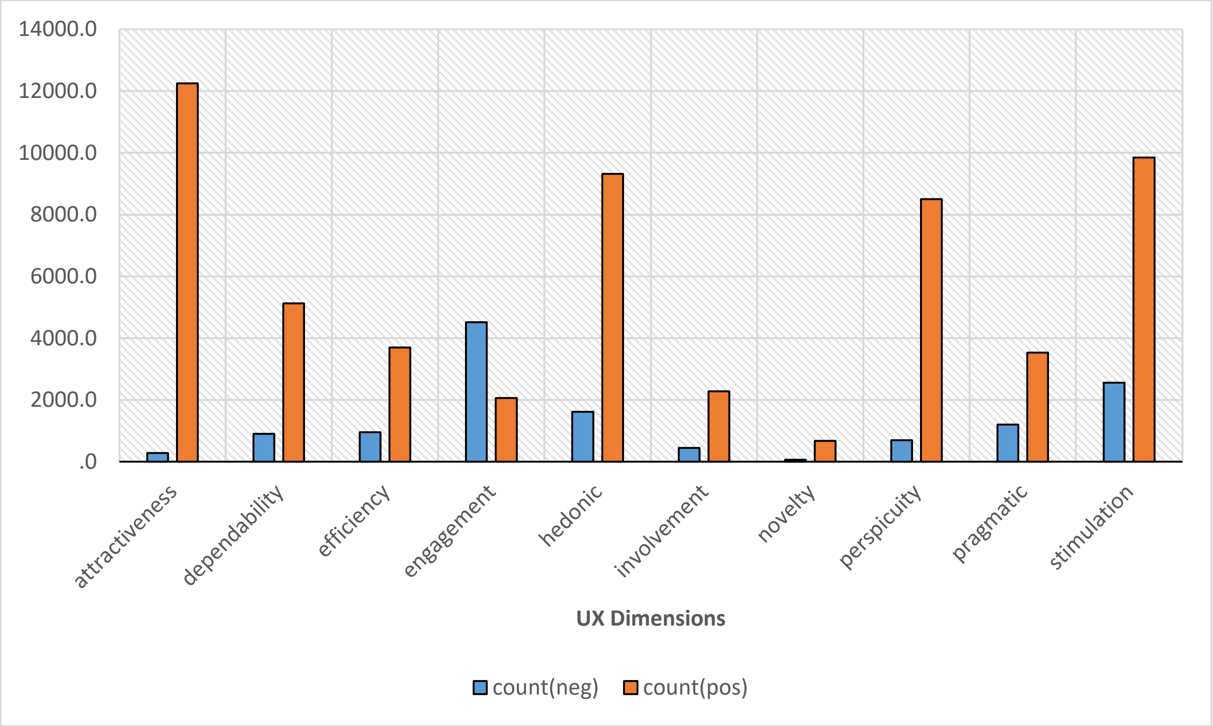


Figure 18: The results of the sentiment orientations of each UXD in all online reviews.

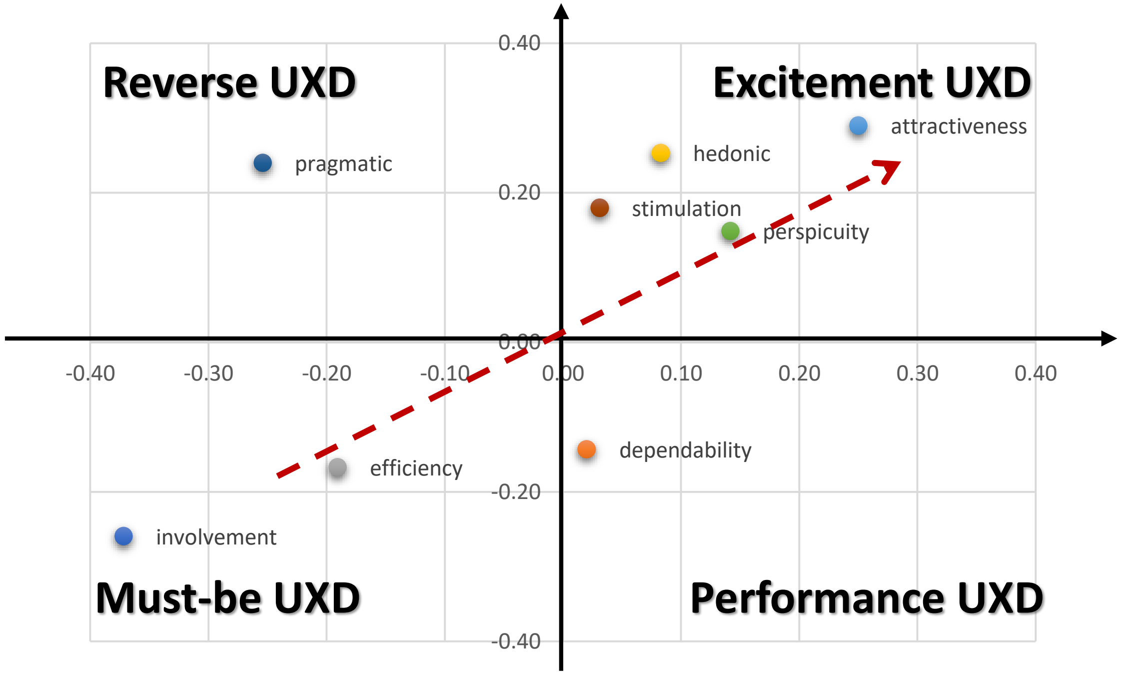


Figure 19: Mapping the extracted dimensions on Kano Model.

UX Contributions & Uniqueness

Contribution

- UX aspects Dictionary Creation
- It proposes a novel knowledge mining method for topic modeling based on word embedding and other similarity computation methods.
- Sentiment orientation and casual effect analysis based on the extracted UX dimensions

Uniqueness

- Proposed methodology to incorporate domain knowledge in LDA based topic extraction model

UX Conclusions and Future Works

UX multi-criteria Qualifiers

- Almost unsupervised approach, only requires a minimal domain aspects configuration per target domain, without requiring additional resources or supervision for UX multi-criteria Qualifiers identification

Topic extractor using Seed words generation and Knowledge Mining methodology

- Proposed method enhancements in LDA framework for capturing useful UX dimensions with higher coherence value, which is **4 timer higher** as compared to existing topic modeling algorithms.

Sentiment Orientation and casual relationships

- The casual relationship of customer sentiment **with 94 % accuracy** toward each UXDs on user satisfaction, an ensemble neural network based model (ENNM)
- User satisfaction Modeling based on Kano Model

Future Works

- Expert based validation
- Consideration of analysis techniques in the current work to for casual relationships between extracted UX dimensions

UX Publication

- Journal
  - **First author: 3**
  - **Co-author: 7**
- Conference
  - **First author: 4**
  - **Co-author: 9**
- Domestic Patient
  - **Register: 1**
  - **Apply: 1**

Total: 25

UX References

1. Law, Effie Lai-Chong, et al. "Understanding, scoping and defining user experience: a survey approach." Proceedings of the SIGCHI conference on human factors in computing systems. ACM, 2009.
2. Law, Effie L-C., and Paul Van Schaik. "Modelling user experience–An agenda for research and practice." Interacting with computers 22.5 (2010): 313-322.
3. Edwards, Jeffrey R., and Richard P. Bagozzi. "On the nature and direction of relationships between constructs and measures." Psychological methods 5.2 (2000): 155.
4. Willett, John B., and Margaret K. Keiley. "Using covariance structure analysis to model change over time." Handbook of applied multivariate statistics and mathematical modeling. Academic Press, 2000. 665-694.
5. Guo, Yue, Stuart J. Barnes, and Qiong Jia. "Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation." Tourism Management 59 (2017): 467-483.
6. Karapanos, Evangelos. "Quantifying diversity in user experience." unpublished doctoral dissertation, Eindhoven University of Technology (2010).
7. Yao, Liang, et al. "Mining coherent topics in documents using word embeddings and large-scale text data." Engineering Applications of Artificial Intelligence 64 (2017): 432-439.
8. Yang, Bai, et al. "Exploiting user experience from online customer reviews for product design." International Journal of Information Management 46 (2019): 173-186.
9. Bilro, Ricardo Godinho, Sandra Maria Correia Loureiro, and João Guerreiro. "Exploring online customer engagement with hospitality products and its relationship with involvement, emotional states, experience and brand advocacy." Journal of Hospitality Marketing & Management 28.2 (2019): 147-171.
10. Liang, Yan, et al. "Extracting topic-sensitive content from textual documents—A hybrid topic model approach." Engineering Applications of Artificial Intelligence 70 (2018): 81-91.
11. Genc-Nayebi, Necmiye, and Alain Abran. "A measurement design for the comparison of expert usability evaluation and mobile app user reviews." (2018): 138-144.
12. Chen, Zhiyuan, and Bing Liu. "Mining topics in documents: standing on the shoulders of big data." Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2014.
13. Mimno, David, et al. "Optimizing semantic coherence in topic models." Proceedings of the conference on empirical methods in natural language processing. Association for Computational Linguistics, 2011.
14. Hassenzahl, Marc, Michael Burmester, and Franz Koller. "AttrakDiff: A questionnaire to measure perceived hedonic and pragmatic quality." Mensch & Computer. 2003.
15. Lavie, Talia, and Noam Tractinsky. "Assessing dimensions of perceived visual aesthetics of web sites." International journal of human-computer studies 60.3 (2004): 269-298.
16. Chen, Zhiyuan, and Bing Liu. "Topic modeling using topics from many domains, lifelong learning and big data." International Conference on Machine Learning. 2014.
17. Chen, Zhiyuan, and Bing Liu. "Mining topics in documents: standing on the shoulders of big data." Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2014.

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References

18. Luo, Yi, and Rebecca Liang Tang. "Understanding hidden dimensions in textual reviews on Airbnb: An application of modified latent aspect rating analysis (LARA)." International Journal of Hospitality Management 80 (2019): 144-154.
19. Chen, Zhiyuan, et al. "Leveraging multi-domain prior knowledge in topic models." Twenty-Third International Joint Conference on Artificial Intelligence. 2013.
20. Ganu, Gayatree, Noemie Elhadad, and Amélie Marian. "Beyond the stars: improving rating predictions using review text content." WebDB. Vol. 9. 2009.
21. Chen, Zhiyuan, and Bing Liu. "Topic modeling using topics from many domains, lifelong learning and big data." International Conference on Machine Learning. 2014.
22. Xu, W., Liu, Y.: mHealthApps: a repository and database of mobile health apps. JMIR MHealth UHealth. 3, e28 (2015).
23. Pang, Bo, Lillian Lee, and Shivakumar Vaithyanathan. "Thumbs up?: sentiment classification using machine learning techniques." Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10. Association for Computational Linguistics, 2002.
24. Blitzer, John, Mark Dredze, and Fernando Pereira. "Biographies, bollywood, boom-boxes and blenders: Domain adaptation for sentiment classification." Proceedings of the 45th annual meeting of the association of computational linguistics. 2007.
25. J. McAuley and J. Leskovec. Hidden factors and hidden topics: understanding rating dimensions with review text. RecSys, 2013.
26. Bi, J.W. et al. 2019. Modelling customer satisfaction from online reviews using ensemble neural network and effect-based Kano model. *International Journal of Production Research*. 0, 0 (2019), 1–21.
27. https://www.kaggle.com/saiamogh/google-play-store-analysis/data
28. Chang, Jonathan, et al. "Reading tea leaves: How humans interpret topic models." Advances in neural information processing systems. 2009.

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Thank you

Questions and Suggestion